

An Implementation of Adaptive Filters with the TMS320C25 or the TMS320C30

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Abstract

Adaptive filtering techniques are necessary considerations when a specific signal output is desired but the coefficients of that filter cannot be determined at the outset. Sometimes this is because of changing line or transmission conditions. An adaptive filter is one which contains coefficients that are updated by an adaptive algorithm to optimize filter response to the desired performance criterion.

Two devices, the TMS320C25 and TMS320C30, combine the power, high speed, flexibility and architecture optimized for adaptive signal processing.

This book discusses the topic of adaptive filter implementation as they apply to these two processors.

The book begins with a description of the two parts of an adaptive filter: the filter and the adaptive algorithm. The book goes on to discuss:

- The applications of adaptive filters (including adaptive prediction, equalization, noise cancellation and echo cancellation).
- The implementation of adaptive structures and algorithms (including transversal structure with the LMS algorithm, symmetric transversal structure, lattice structure, and modified LMS algorithms)
- Implementation considerations (including dynamic range constraint, finite precision errors, and design issues)



- ❑ Software development (assembly function libraries, C function libraries, development process and environment)

The book also contains:

- ❑ Tables showing transversal structure, symmetric transversal structure and lattice structure for both the TMS320C25 and TMS320C30 processors
- ❑ Extensive references
- ❑ Multiple appendices of sample code for both TMS320C25 and TMS320C30 processors



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Introduction

A filter selects or controls the characteristics of the signal it produces by conditioning the incoming signal. The coefficients of the filter determine its characteristics and output *a priori* in many cases. Often, a specific output is desired, but the coefficients of the filter cannot be determined at the outset. An example is an echo canceller; the desired output cancels the echo signal (an output result of zero when there is no other input signal). In this case, the coefficients cannot be determined initially since they depend on changing line or transmission conditions. For applications such as this, it is necessary to rely on adaptive filtering techniques.

An adaptive filter is a filter containing coefficients that are updated by an adaptive algorithm to optimize the filter's response to a desired performance criterion. In general, adaptive filters consist of two distinct parts: a filter, whose structure is designed to perform a desired processing function; and an adaptive algorithm, for adjusting the coefficients of that filter to improve its performance, as illustrated in Figure 1. The incoming signal, $x(n)$, is weighted in a digital filter to produce an output, $y(n)$. The adaptive algorithm adjusts the weights in the filter to minimize the error, $e(n)$, between the filter output, $y(n)$, and the desired response of the filter, $d(n)$. Because of their robust performance in the unknown and time-variant environment, adaptive filters have been widely used from telecommunications to control.

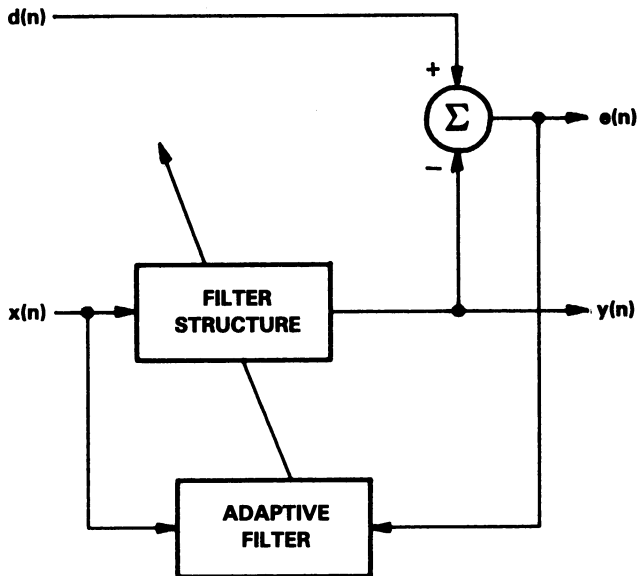


Figure 1. General Form of an Adaptive Filter

Adaptive filters can be used in various applications with different input and output configurations. In many applications requiring real-time operation, such as adaptive prediction, channel equalization, echo cancellation, and noise cancellation, an adaptive filter implementation based on a programmable digital signal processor (DSP) has many advantages over other approaches such as a hard-wired adaptive filter. Not only are power, space, and manufacturing requirements greatly reduced, but also programmability provides flexibility for system upgrade and software improvement.

The early research on adaptive filters was concerned with adaptive antennas [1] and adaptive equalization of digital transmission systems [2]. Much of the reported research on the adaptive filter has been based on Widrow's well-known Least Mean Square (LMS) algorithm, because the LMS algorithm is relatively simple to design and implement, and it is well-understood and well-suited for many applications. All the filter structures and update algorithms discussed in this application report are Finite Impulse Response (FIR) filter structures and LMS-type algorithms. However, for a particular application, adaptive filters can be implemented in a variety of structures and adaptation algorithms [1, 3 through 9]. These structures and algorithms generally trade increased complexity for improved performance. An interactive software package to evaluate the performance of adaptive filters has also been developed [10].

The complexity of an adaptive filter implementation is usually measured in terms of its multiplication rate and storage requirement. However, the data flow and data manipulation capabilities of a DSP are also major factors in implementing adaptive filter systems. Parallel hardware multiplier, pipeline architecture, and fast on-chip memory size are major features of most DSPs [11, 12] and can make filter implementation more efficient.

Two such devices, the TMS320C25 and TMS320C30 from Texas Instruments [13, 14], have been chosen as the processors for fixed-point and floating-point arithmetic. They combine the power, high speed, flexibility, and an architecture optimized for adaptive signal processing. The instruction execution time is 80 ns for the TMS320C25 and only 60 ns for the TMS320C30. Most instructions execute in a single cycle, and the architectures of both processors make it possible to execute more than one operation per instruction. For example, in one instruction, the TMS320C25 processor can generate an instruction address and fetch that instruction, decode the instruction, perform one or two data moves (if the second data is from program memory), update one address pointer, and perform one or two computations (multiplication and accumulation). These processors are designed for real-time tasks in telecommunications, speech processing, image processing, and high-speed control, etc.

To direct the present research toward realistic real-time applications, three adaptive structures were implemented:

1. Transversal
2. Symmetric transversal
3. Lattice

Each structure utilizes five different update algorithms:

1. LMS
2. Normalized LMS
3. Leaky LMS
4. Sign-error LMS
5. Sign-sign LMS

Each structure with its adaptation algorithms is implemented using the TMS320C25 with fixed-point arithmetic and the TMS320C30 with floating-point arithmetic. The processor assembly code is included in the Appendix for each implementation. The assembly code for each structure and adaptation strategy can be readily modified by the reader to fit his/her applications and could be incorporated into a C function library as callable routines.

In this application report, the applications of adaptive filters, such as adaptive prediction, adaptive equalization, adaptive echo cancellation, and adaptive noise cancellation are presented first. Next, the implementation of the three filter structures and five adaptive algorithms with the TMS320C25 and TMS320C30 is described. This is followed by the practical considerations on the implementation of these adaptive filters. The remainder of the application report covers coding options, such as the routine libraries that support both assembly and C languages.

Applications of Adaptive Filters

The most important feature of an adaptive filter is the ability to operate effectively in an unknown environment and track time-varying characteristics of the input signal. The adaptive filter has been successfully applied to communications, radar, sonar, control, and image processing. Figure 1 illustrates a general form of an adaptive filter with input signals, $x(n)$ and $d(n)$, output signal, $y(n)$, and error signal, $e(n)$, which is the difference between the desired signal, $d(n)$, and output signal, $y(n)$. The adaptive filter can be used in different applications with different input/output configurations. In this section we briefly discuss several potential applications for the adaptive filters [15].

Adaptive Prediction

Adaptive prediction [16 through 18] is illustrated in Figure 2. In the general application of adaptive prediction, the signals are $x(n)$ – delayed version of original signal, $d(n)$ – original input signal, $y(n)$ – predicted signal, and $e(n)$ – prediction error or residual.

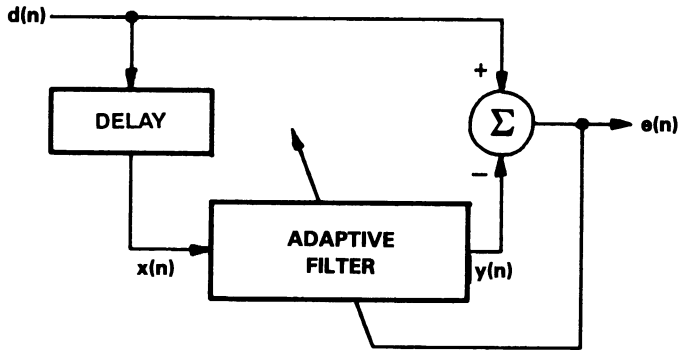


Figure 2. Block Diagram of an Adaptive Predictor

A major application of the adaptive prediction is the waveform coding of a speech signal. The adaptive filter is designed to exploit the correlation between adjacent samples of the speech signal so that the prediction error is much smaller than the input signal on the average. This prediction error signal is quantized and sent to the receiver in order to reduce the number of bits required for the transmission. This type of waveform coding is called Adaptive Differential Pulse-Code Modulation (ADPCM) [17] and provides data rate compression of the speech at 32 kb/s with toll quality. More recently, in certain on-line applications, time recursive modeling algorithms have been proposed to facilitate speech modeling and analysis.

The coefficients of the adaptive predictor can be used as the autoregressive (AR) parameters of the nonstationary model. The equation of the AR process is

$$u(n) = a_1 * u(n-1) + a_2 * u(n-2) + \dots + a_m * u(n-m) + v(n)$$

where a_1, a_2, \dots, a_m are the AR parameters. Thus, the present value of the process $u(n)$ equals a finite linear combination of past values of the process plus an error term $v(n)$. This adaptive AR model provides a practical means to measure the instantaneous frequency of input signal. The adaptive predictor can also be used to detect and enhance a narrow band signal embedded in broad band noise. This Adaptive Line Enhancer (ALE) provides at its output $y(n)$ a sinusoid with an enhanced signal-to-noise ratio, while the sinusoidal components are reduced at the error output $e(n)$.

Adaptive Equalization

Figure 3 shows another model known as adaptive equalization [2, 9, 15]. The signals in the adaptive equalization model are defined as $x(n)$ – received signal (filtered version of transmitted signal) plus channel noise, $d(n)$ – detected data signal (data mode) or pseudo random number (training mode), $y(n)$ – equalized signal used to detect received data, and $e(n)$ – residual intersymbol interference plus noise.

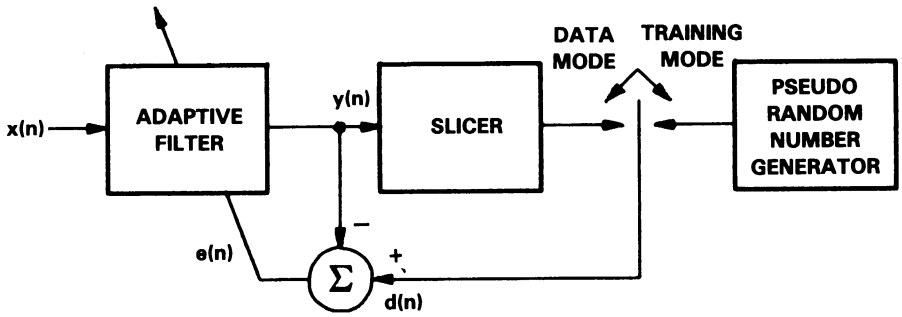


Figure 3. Block Diagram of an Adaptive Equalizer

The use of adaptive equalization to eliminate the amplitude and phase distortion introduced by the communication channel was one of the first applications of adaptive filtering in telecommunications [19]. The effect of each symbol transmitted over a time-dispersive channel extends beyond the time interval used to represent that symbol, resulting in an overlay of received symbols. Since most channels are time-varying and unknown in advance, the adaptive channel equalizer is designed to deal with this intersymbol interference and is widely used for bandwidth-efficient transmission over telephone and radio channels.

Adaptive Echo Cancellation

Another application, known as adaptive echo cancellation [20, 21] is shown in Figure 4. In this application, the signals are identified as $x(n)$ – far-end signal, $d(n)$ – echo of far-end signal plus near-end signal, $y(n)$ – estimated echo of far-end signal, and $e(n)$ – near-end signal plus residual echo.

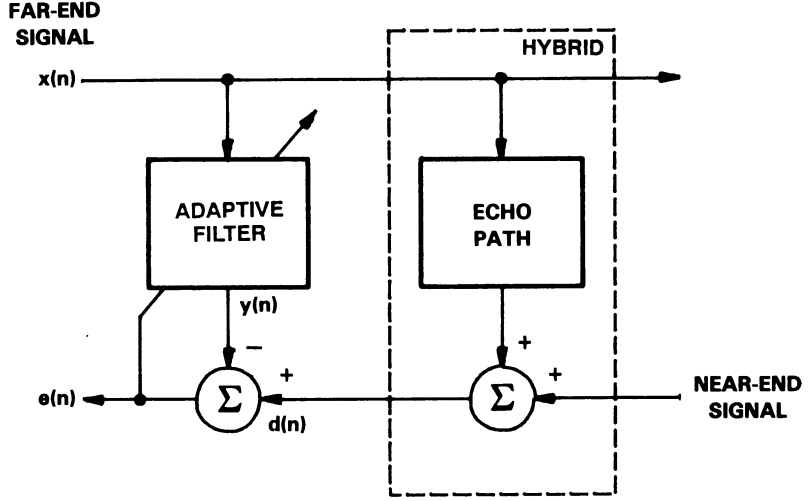


Figure 4. Block Diagram of an Echo Canceller

The adaptive echo cancellers are used in practical applications of cancelling echoes for long-distance telephone voice communication, full-duplex voiceband data modems, and high-performance audio-conferencing systems. To overcome the echo problem, echo cancellers are installed at both ends of the network. The cancellation is achieved by estimating the echo and subtracting it from the return signal.

Adaptive Noise Cancellation

One of the simplest and most effective adaptive signal processing techniques is adaptive noise cancelling [1, 22]. As shown in Figure 5, the primary input $d(n)$ contains both signal and noise, where $x(n)$ is the noise reference input. An adaptive filter is used to estimate the noise in $d(n)$ and the noise estimate $y(n)$ is then subtracted from the primary channel. The noise cancellation output is then the error signal $e(n)$.

The applications of noise cancellation include the cancellation of various forms of interference in electrocardiography, noise in speech signals, noise in fighter cockpit environments, antennas sidelobe interference, and the elimination of 60-Hz hum. In the majority of these noise cancellation applications, the LMS algorithm has been utilized.

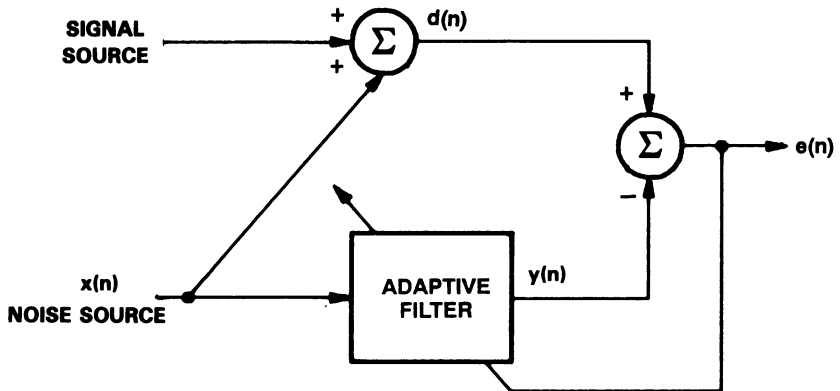


Figure 5. General Form of a Noise Canceller

Application Summary

The above list of applications is not exhaustive and is limited primarily to applications within the field of telecommunications. Adaptive filtering has been used extensively in the context of many other fields including, but not limited to, instantaneous frequency tracking, intrusion detection, acoustic Doppler extraction, on-line system identification, geophysical signal processing, biomedical signal processing, the elimination of radar clutter, beamforming, sonar processing, active sound cancellation, and adaptive control.

Implementation of Adaptive Structures and Algorithms

Several types of filter structures can be implemented in the design of the adaptive filters such as Infinite Impulse Response (IIR) or Finite Impulse Response (FIR). An adaptive IIR filter [1, 5], with poles as well as zeros, makes it possible to offer the same filter characteristics as the FIR filter with lower filter complexity. However, the major problem with adaptive IIR filter is the possible instability of the filter if the poles move outside the unit circle during the adaptive process. In this application report, only FIR structure is implemented to guarantee filter stability.

An adaptive FIR filter can be realized using transversal, symmetric transversal, and lattice structures. In this section, the adaptive transversal filter with the LMS algorithm is introduced and implemented first to provide a working knowledge of adaptive filters.

Transversal Structure with LMS Algorithm

Transversal Structure Filter

The most common implementation of the adaptive filter is the transversal structure (tapped delay line) illustrated in Figure 6. The filter output signal $y(n)$ is

$$y(n) = \underline{w}^T(n)\underline{x}(n) = \sum_{i=0}^{N-1} w_i(n) x(n-i) \quad (1)$$

where $\underline{x}(n)=[x(n) \ x(n-1) \ \dots \ x(n-N+1)]^T$ is the input vector, $\underline{w}(n)=[w_0(n) \ w_1(n) \ \dots \ w_{N-1}(n)]^T$ is the weight vector, T denotes transpose, n is the time index, and N is the order of filter. This example is in the form of a finite impulse response filter as well as the convolution (inner product) of two vectors $\underline{x}(n)$ and $\underline{w}(n)$. The implementation of Equation (1) is illustrated using the following C program:

```
y[n] = 0.;
for (i = 0; i < N; i++) {
    y[n] += wn[i]*xn[i];
}
```

where $wn[i]$ denotes $w_i(n)$ and $xn[i]$ represents $x(n-i)$.

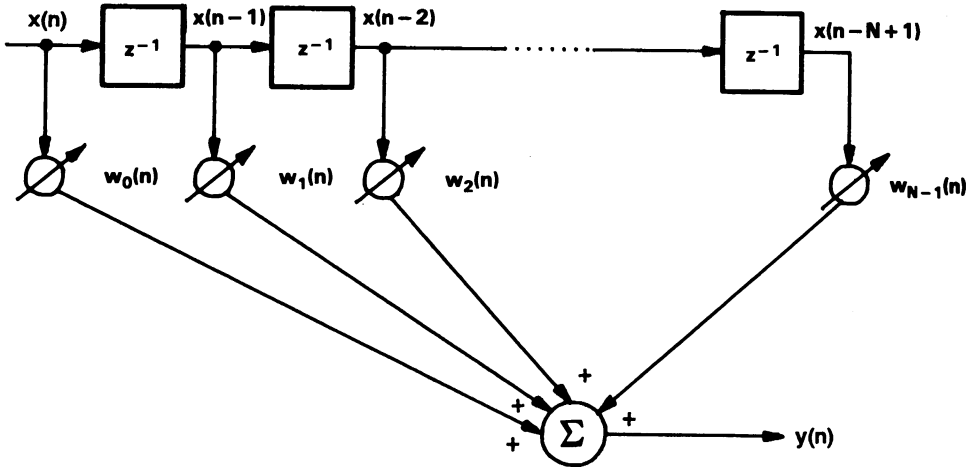


Figure 6. Transversal Filter Structure

TMS320C25 Implementation

The architecture of TMS320C25 [13] is optimized to implement the FIR filter. After execution of the CNFP (Configure Block B0 as Program Memory) instruction, the filter coefficients $w_i(n)$ from RAM block B0 (via program bus) and data $x(n-i)$ from RAM block B1 (via data bus) are available simultaneously for the parallel multiplier (see Figure 7).

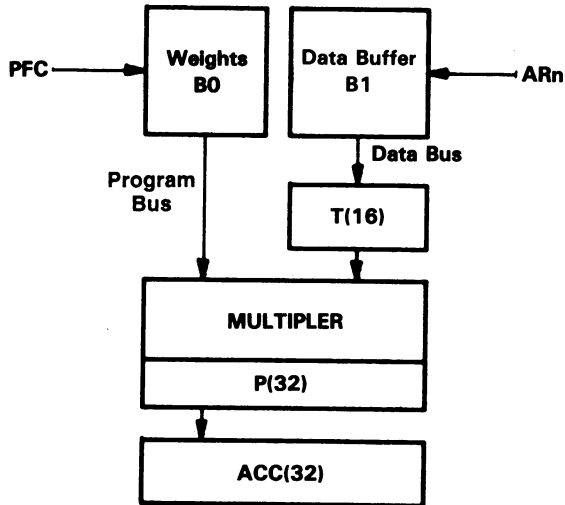
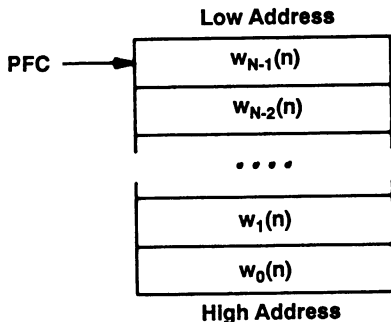


Figure 7. TMS320C25 Arithmetic Unit (after execute CNFP instruction)

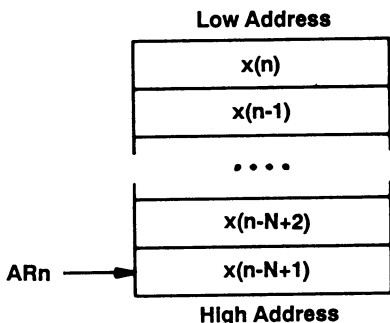
The MACD instruction enables complete multiply/accumulate, data move, and pointer update operations to be completed in a single instruction cycle (80 ns) if filter coefficients are stored in on-chip RAM or ROM or in off-chip program memory with zero wait states. Since the adaptive weights $w_i(n)$ need to be updated in every iteration, the filter coefficients must be stored in RAM. The implementation of the inner product in Equation (1) can be made even more efficient with a repeat instruction, RPTK. An N-weight transversal filter can be implemented as follows [23]:

LARP	ARn	
LRLK	ARn, LASTAP	
RPTK	N-1	
MACD	COEFFP, *-	(A)

Where ARn is an auxiliary address register that points to $x(n-N+1)$, and the Prefetch Counter (PFC) points to the last weight $w_{N-1}(n)$ indicated by COEFFP. When the MACD instruction is repeated, the coefficient address is transferred to the PFC and is incremented by one during its operation. Therefore, the components of weight vector $\underline{w}(n)$ are stored in B0 as



The MACD in repeat mode will also copy data pointed to by ARn, to the next higher on-chip RAM location. The buffer memories of transversal filter are therefore stored as



In general, roundoff noise occurs after each multiplication. However, the TMS320C25 has a 16×16 -bit multiplier and a 32-bit accumulator, so there is no roundoff during the summing of a set of product terms in Program (A). All multiplication products are represented in full precision, and rounding is performed after they are summed. Thus $y(n)$ is obtained from the accumulator with only one roundoff, which minimizes the roundoff noise in the output $y(n)$. Since both the tapped delay line and the adaptive weights are stored in data RAM to achieve the fastest throughput, the highest transversal filter order for efficient implementation on the TMS320C25 is 256. However, if necessary, higher order filters can be implemented by using external data RAM.

TMS320C30 Implementation

The architecture of TMS320C30 [14] is quite different from TI's second generation processors. Instead of using program/data memory, it provides two data address buses to do the data memory manipulations. This feature allows two data memory addresses to be generated at the same time. Hence, parallel data store, load, or one data store with one data load can be done simultaneously. Such capabilities make the programming much easier and more flexible. Since the hardware multiplier and arithmetic logic unit (ALU) of TMS320C30 are separated, with proper operand arrangement, the processor can do one multiplication and one addition or subtraction at the same time. With these two combined features, the TMS320C30 can execute several other parallel instructions. These parallel instructions can be found in Section 11 of the *Third-Generation TMS320 User's Guide* [14]. Associating with single repeat instruction RPTS, an inner product in Equation (1) can be implemented as follows:

MPYF3	*AR0++(1)%,*AR1++(1)%	R1	; w[0].x[0]
RPTS	N-2		; Repeat N-1 times
MPYF3	*AR0++(1)%,*AR1++(1)%	R1	; y[] = w[].x[]
	ADDF3	R1,R2,R2	
	ADDF3	R1,R2,R2	; Include last product

where auxiliary registers AR0 and AR1 point to x and w arrays. The addition in the parallel instruction sums the previous values of R1 and R2. Therefore, R1 is initialized with the first product prior to the repeat instruction RPTS.

Note that the implementation above does not move the data in the x array like MACD does in TMS320C25. For filter delay taps, the TMS320C30 uses a circular buffer method to implement the delay line. This method reserves a certain size of memory for the buffer and uses a pointer to indicate the beginning of the buffer. Instead of moving data to next memory location, the pointer is updated to point to the previous memory location. Therefore, from the new beginning of the buffer, it has the effect of the tapped delay line. When the value of the pointer exceeds the end of the buffer, it will be circled around to the other end of the buffer. It works just like joining two ends of the buffer together as a necklace. Thus, new data is within the circular queue, pointed to by AR0, replacing

the oldest value. However, from an adaptive filter point of view, data doesn't have to be moved at this point yet.

TMS320C30 has a 32-bit floating point multiplier and the result from the multiplier is put and accumulated into a 40-bit extended precision register. If the input from A/D converter is equal to or less than 16 bits, there is no roundoff noise after multiplication. Theoretically, the TMS320C30 can implement a very high order of adaptive filter. However, for the most efficient implementation, the limitation of filter order is 2K because the TMS320C30 external data write requires at least two cycles. If the filter coefficients are put in somewhere other than internal data RAM, the instruction cycles will be increased.

LMS Adaptation Algorithm

The adaptation algorithm uses the error signal

$$e(n) = d(n) - y(n), \quad (2)$$

where $d(n)$ is the desired signal and $y(n)$ is the filter output. The input vector $\underline{x}(n)$ and $e(n)$ are used to update the adaptive filter coefficients according to a criterion that is to be minimized. The criterion employed in this section is the mean-square error (MSE) ϵ :

$$\epsilon = E[e^2(n)] \quad (3)$$

where $E[.]$ denotes the expectation operator. If $y(n)$ from Equation (1) is substituted into Equation (2), then Equation (3) can be expressed as

$$\epsilon = E[d^2(n)] + \underline{w}^T(n)R\underline{w}(n) - 2 \underline{w}^T(n)\underline{p} \quad (4)$$

where $R = E[\underline{x}(n)\underline{x}^T(n)]$ is the $N \times N$ autocorrelation matrix, which indicates the sample-to-sample correlation within a signal, and $\underline{p} = E[d(n)\underline{x}(n)]$ is the $N \times 1$ cross-correlation vector, which indicates the correlation between the desired signal $d(n)$ and the input signal vector $\underline{x}(n)$.

The optimum solution $\underline{w}^* = [w_0^* \ w_1^* \ \dots \ w_{N-1}^*]^T$, which minimizes MSE, is derived by solving the equation

$$\frac{\delta \epsilon}{\delta \underline{w}(n)} = 0 \quad (5)$$

This leads to the normal equation

$$R \underline{w}^* = \underline{p} \quad (6)$$

If the R matrix has full rank (i.e., R^{-1} exists), the optimum weights are obtained by

$$\underline{w}^* = R^{-1} \underline{p} \quad (7)$$

In Linear Predictive Coding (LPC) of a speech signal, the input speech is divided into short segments, the quantities of R and \underline{p} are estimated, and the optimal weights corresponding to each segment are computed. This procedure is called a block-by-block data-adaptive algorithm [24].

A widely used LMS algorithm is an alternative algorithm that adapts the weights on a sample-by-sample basis. Since this method can avoid the complicated computation of R^{-1} and \underline{p} , this algorithm is a practical method for finding close approximate solutions to Equation (7) in real time. The LMS algorithm is the steepest descent method in which the next weight vector $w(n+1)$ is increased by a change proportional to the negative gradient of mean-square-error performance surface in Equation (7)

$$\underline{w}(n+1) = \underline{w}(n) - u \underline{\nabla}(n) \quad (8)$$

where u is the adaptation step size that controls the stability and the convergence rate. For the LMS algorithm, the gradient at the n th iteration, $\underline{\nabla}(n)$, is estimated by assuming squared error $e^2(n)$ as an estimate of the MSE in Equation (3). Thus, the expression for the gradient estimate can be simplified to

$$\underline{\nabla}(n) = \frac{\delta[e^2(n)]}{\delta \underline{w}(n)} = -2 e(n) \underline{x}(n) \quad (9)$$

Substitution of this instantaneous gradient estimate into Equation (8) yields the Widrow-Hoff LMS algorithm

$$\underline{w}(n+1) = \underline{w}(n) + 2 u e(n) \underline{x}(n) \quad (10)$$

where $2 u$ in Equation (10) is usually replaced by u in practical implementation.

Starting with an arbitrary initial weight vector $\underline{w}(0)$, the weight vector $\underline{w}(n)$ will converge to its optimal solution \underline{w}^* , provided u is selected such that [1]

$$0 < u < \frac{1}{\lambda_{\max}} \quad (11)$$

where λ_{\max} is the largest eigenvalue of the matrix R . λ_{\max} can be bounded by

$$\lambda_{\max} < \text{Tr} [R] = \sum_{i=0}^{N-1} r(i) = N r(0) \quad (12)$$

where $\text{Tr} [.]$ denotes the trace of a matrix and $r(0) = E [x^2(n)]$ is average input power.

For adaptive signal processing applications, the most important practical consideration is the speed of convergence, which determines the ability of the filter to track nonstationary signals. Generally speaking, weight vector convergence is attained only when the slowest weight has converged. The time constant of the slowest mode is [1]

$$t = \frac{1}{u\lambda_{\min}} \quad (13)$$

This indicates that the time constant for weight convergence is inversely proportional to u and also depends on the eigenvalues of the autocorrelation matrix of the input. With the disparate eigenvalues, i.e., $\lambda_{\max} \gg \lambda_{\min}$, the setting time is limited by the slowest mode, λ_{\min} . Figure 8 shows the relaxation of the mean square error from its initial value ϵ_0 toward the optimal value ϵ_{\min} .

Adaptation based on a gradient estimate results in noise in the weight vector, therefore a loss in performance. This noise in the adaptive process causes the steady state weight vector to vary randomly about the optimum weight vector. The accuracy of weight vector in steady state is measured by excess mean square error (excess MSE = $E [\epsilon - \epsilon_{\min}]$). The excess MSE in the LMS algorithm [1] is

$$\text{excess MSE} = u \text{Tr}[R] \epsilon_{\min} \quad (14)$$

where ϵ_{\min} is minimum MSE in the steady state.

Equations (13) and (14) yield the basic trade-off of the LMS algorithm: to obtain high accuracy (low excess MSE) in the steady state, a small value of u is required, but this will slow down the convergence rate. Further discussions of the characteristics and properties of the LMS algorithm are presented in [1, 3 through 9]. The implementations of LMS algorithm with the TMS320C25 and TMS320C30 are presented next.

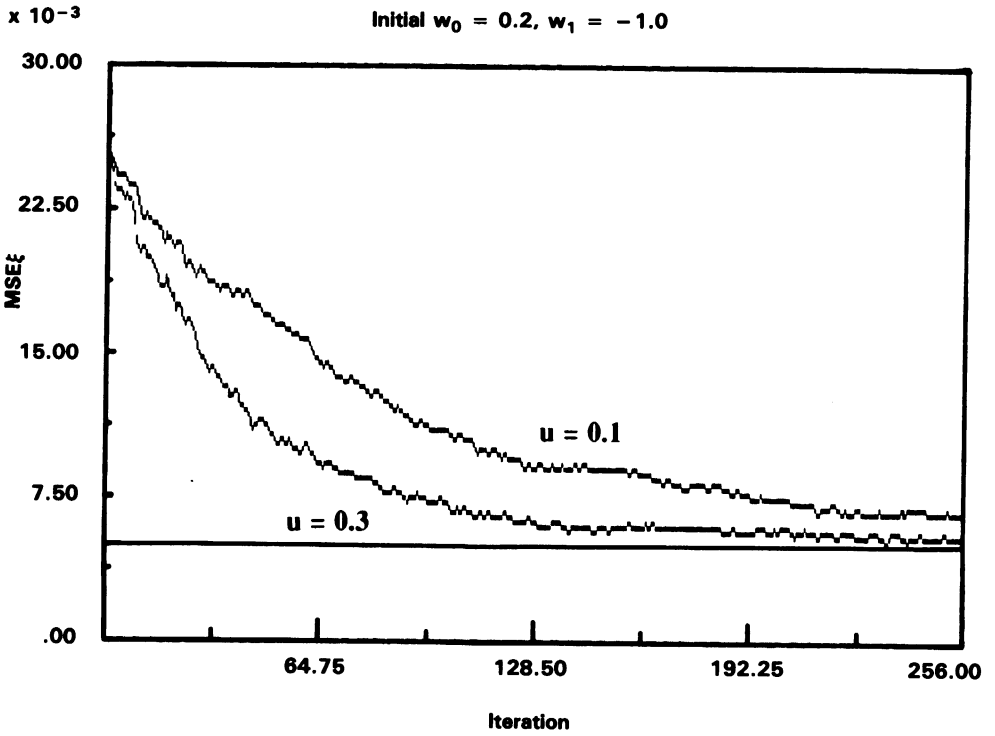


Figure 8. Learning Curve of an Adaptive Transversal Filter and an LMS Algorithm with Different Step Sizes

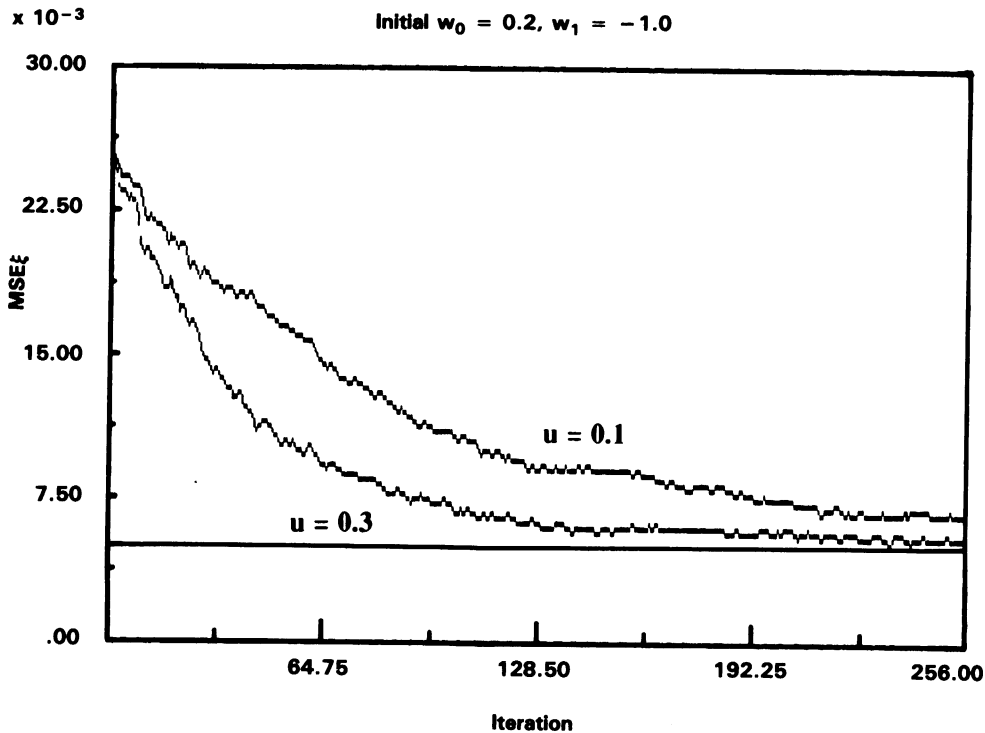


Figure 8. Learning Curve of an Adaptive Transversal Filter and an LMS Algorithm with Different Step Sizes

Since $u^*e(n)$ is constant for N weights update, the error signal $e(n)$ is first multiplied by u to get $ue(n)$. This constant can be computed first and then multiplied by $x(n)$ to update $w(n)$. An implementation method of the LMS algorithm in Equation (10) is illustrated as

```

ue(n) = u*e[n];
for (i=0; i<N; i++) {
    wn[i] += uen * xn[i];
}

```

TMS320C25 Implementation

The TMS320C25 provides two powerful instructions (ZALR and MPYA) to perform the update example in Equation (10).

- ZALR loads a data memory value into the high-order half of the accumulator while rounding the value by setting bit 15 of the accumulator to one and setting bits 0-14 of the accumulator to zero. The rounding is necessary because it can reduce the roundoff noise from multiplication.
- MPYA accumulates the previous product in the P register and multiplies the operand with the data in T register.

Assuming that $ue(n)$ is stored in T and the address pointer is pointing to AR3, the adaptation of each weight is shown in the following instruction sequence:

```

LRLK  AR1,N-1           ; Initialize loop counter
LRLK  AR2,COEFFD        ; Point to  $w_{N-1}(n)$ 
LRLK  AR3,LASTAP+1     ; Point to  $x(n-N+1)$ , since MACD in (A)
                                ; Already moved elements of current
                                ;  $x(n)$  to the next higher location
ADAP  MPY  *-,AR2        ;  $P=ue(n) * x(n-N+1)$ 
      ZALR *,AR3         ; Load  $w_i(n)$  and round
      MPYA *-,AR2        ;  $ACC=P+w_i(n)$  and  $P=ue(n) * x(n-i)$ 
      SACH *+,0,AR1      ; Store  $w_i(n+1)$ 
      BANZ ADAP,*-,AR2   ; Test loop counter, if counter not
                                ; Equal to 0, decrement counter,
                                ; Branch to ADAP and select AR2 as
                                ; Next pointer.

```

For each iteration, N instruction cycles are needed to perform Equation (1), $6N$ instruction cycles are needed to perform weight updates in Equation (10), and the total number of instruction cycles needed is $7N+28$. An example of a TMS320C25 program implementing a LMS transversal filter is presented in Appendix A1. Note that BANZ needs three instruction cycles to execute. This can be avoided by using straight line code, which requires $4N+33$ instruction cycles [25].

TMS320C30 Implementation

Although the TMS320C30 doesn't provide any specific instruction for adaptive filter coefficients update, it still can achieve the weight updating in two instructions because of its powerful architecture. The TMS320C30 has a repeat block instruction RPTB, which allows a block of instructions to be repeated a number of times without any penalty for looping. A single repeat mode, RM, in the status register, ST, and three registers – repeat start address (RS), repeat end address (RE), and repeat counter (RC) – control the block repeat. When RM is set, the PC repeats the instructions between RS and RE a number of times, which is determined by the value of RC. The repeat modes repeat a block of code at least once in a typical operation. The repeat counter should be loaded with one less than the desired number of repetitions. Assuming the error signal $e(n)$ in Equation (10) is stored in R7, the adaptation of filter coefficients is shown as follows:

```

MPYF3 *AR0++(1),R7,R1 ; R1 = u*e(n)*x(n)
LDI   order-3,RC      ; Initialize repeat counter
RPTB  LMS              ; Do i = 0, N-3
MPYF3 *AR0++(1),R7,R1 ; Compute u*e(n)*x(n-i)
| |ADDF3 *AR1,R1,R2    ; Compute wi(n) + u*e(n)*x(n-i)
LMS   STF   R2,*AR1++(1)% ; Store wi(n+1)

MPYF3 *AR0,R7,R1      ; For i = N-2
| |ADDF3 *AR1,R1,R2
STF   R2,*AR1++(1)%  ; Store wN-2(n+1)
ADDF3 *AR1,R1,R2     ; Include last w
STF   R2,*AR1++(1)%  ; Store wN-1(n+1)

```

where auxiliary register AR0 and AR1 point to x and w arrays. R1 is updated before loop since the accumulation in the parallel instruction uses the previous value in R1. In order to update x array pointer to the new beginning of the data buffer for next iteration (i.e., perform the data move), one of the loop instruction set has been taken out of loop and modified by eliminating the incrementation of AR0.

To perform an N-weight adaptive LMS transversal filter on TMS320C30 requires $3N+15$ instruction cycles. There are N and $2N$ instruction cycles to perform Equations (1) and (10), respectively. The TMS320C30 example program is given in Appendix A2.

The LMS algorithm considerably reduces the computational requirements by using a simplified mean square error estimator (an estimate of the gradient). This algorithm has proved useful and effective in many applications. However, it has several limitations in performance such as the slow initial convergence, the undesirable dependence of its convergence rate on input signal statistics, and an excess mean square error still in existence after convergence.

Symmetric Transversal Structure [5]

A transversal filter with symmetric impulse response (weight values) about the center weight has a linear phase response. In applications such as speech processing, linear phase filters are preferred since they avoid phase distortion by causing all the components in the filter input to be delayed by the same amount. The adaptive symmetric transversal structure is shown in Figure 9.

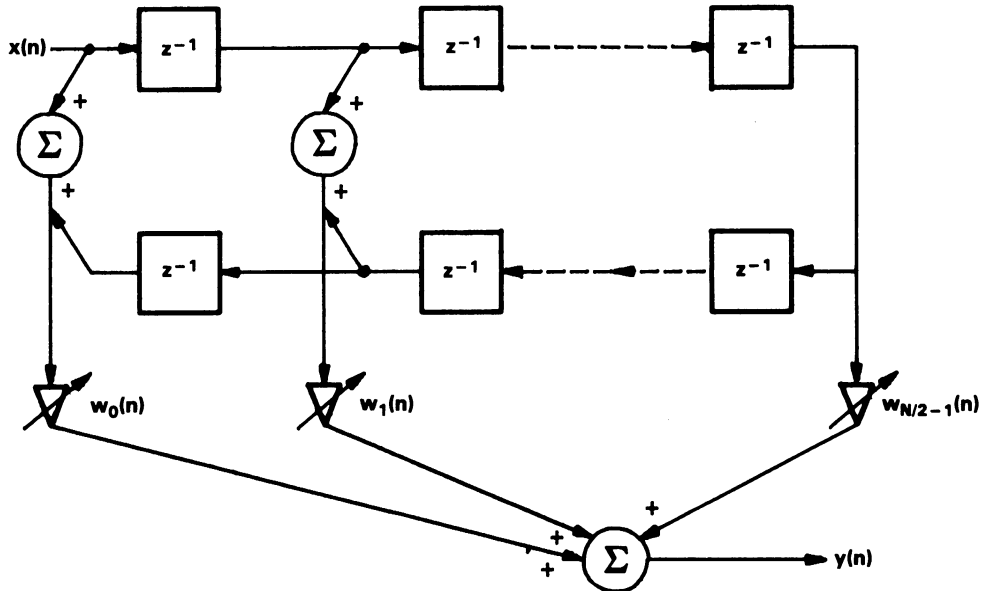


Figure 9. Symmetric Transversal Structure (even order)

This filter is actually an FIR filter with an impulse response that is symmetric about the center tap. The output of the filter is obtained as

$$y(n) = \sum_{i=0}^{N/2-1} w_i(n) [x(n-i) + x(n-N+i+1)] \quad (15a)$$

where N is an even number. Note that, for fixed-point processors, the addition in the brackets may introduce overflow because the input signals $x(n-i)$ and $x(n-N+i+1)$ are in the range of -1 and $1-2^{-15}$. This problem can be solved by shifting $x(n)$ to the right one bit. The update of the weight vector is

$$w_i(n+1) = w_i(n) + ue(n)[x(n-1) + x(n-N+i+1)] \quad (15b)$$

for $i=0,1,\dots,(N/2-1)$, which requires $N/2$ multiplications and N additions. Theoretically, this symmetric structure can also reduce computational complexity since such filters require only half the multiplications of the general transversal filter. However, it is true only for the TMS320C30 processor. When a filter is implemented on the TMS320C25, the transversal structure is more efficient than the symmetric transversal structure due to the pipeline multiplication and accumulation instruction MACD, which is optimized to implement convolution in Equation (1).

TMS320C25 Implementation

For TMS320C25, in order to implement the instructions MAC, ZALR, and MPYA, we can trade memory requirements for computation saving by defining

$$z(n-i) = x(n-i) + x(n-N+i+1), \quad i=0,1,\dots,N/2-1 \quad (16a)$$

Now, Equation (15) can be expressed as

$$y(n) = \sum_{i=0}^{N/2-1} w_i(n) z(n-i) \quad (16b)$$

$$w_i(n+1) = w_i(n) + u e(n) z(n-i), \quad i=0,1,\dots,N/2-1 \quad (16c)$$

Equation (16a) can be implemented using the TMS320C25 as

	LARK	AR1, N/2-1	; Counter = N/2 -1
	LRLK	AR2, LAST_X	; Point to $x(n-N+1)$
	LRLK	AR3, FIRST_X	; Point to $x(n)$
	LRLK	AR4, FIRST_Z	; Point to $z(n)$
	LARP	AR3	
SYM	LAC	*+,0,AR2	
	ADD	*-,0,AR4	
	SACL	*+,0,AR1	
	BANZ	SYM,*-,AR3	

The instruction sequence to implement the LMS algorithm in Equations (1) and (10) can be used to implement Equations (16b) and (16c), except using MAC instead of MACD in Program (A). Therefore, N instruction cycles are needed to shift data in $x(n)$, $3N$ instruction cycles are needed to implement Equation (16a), $N/2$ for Equation (16b), and $3N$ for Equation (16c). The total number of instruction cycles required to implement the symmetric transversal filter with the LMS algorithm is $7.5N+38$. Where $7.5N$ is an integer because N is chosen as an even number. The $0.5N$ instruction cycles come from Equation (15a) since symmetric transversal structure folds the filter taps into half of the order N (see Figure 9). The maximum filter length for most efficient code, 256, is the

same as for the FIR filter. The use of the additional data memory can be obtained from the reduced data memory requirement for weights of the symmetric transversal filter. The complete TMS320C25 program is given in Appendix B1.

Note that instead of storing buffer locations $x(n)$ contiguously, then using DMOV to shift data in the buffer memory (requiring N cycles) at the end of each iteration, we can use a circular buffer with pointers pointing to $x(n)$ and $x(n-N+1)$. Since pointer updating requires several instruction cycles, compared with N cycles using DMOV to update the buffer memory contents, the circular buffer technique is more efficient if N is large.

TMS320C30 Implementation

As mentioned above, the TMS320C30 uses a circular buffer instead of data move technique. Therefore, it does not have to implement tapped delay line separately as TMS320C25. Equations (1) and (16a) can be combined and implemented in the same loop. The advantage of this is that a parallel instruction reduces the number of the instruction cycles. The implementation is shown as follows:

```

LDF      0.0,R2                ; Clear R2
LDI      order/2-2,RC          ; Set up loop counter
RPTB    INNER                  ; Do i = 0, N/2 -2
ADDF3   *AR4++(1%)*AR5--(1%),R1 ; z(i) = x(n-i) + x(n+N-i)
MPYF3   R1,*AR1++(1),R3        ; R3 = w[] * z[]
| | STF  R1,*AR2++(1)           ; Store z(i)
INNER   ADDF3  R3,R2,R2         ; Accumulate the result for y

ADDF3   *AR4++(1%)*AR5--(1%),R1 ; For i = N/2 -1
MPYF3   R1,*AR1--(IR0),R3
| | STF  R1,*AR2--(IR0)
ADDF3   R3,R2,R2                ; Include last product

```

where AR4 and AR5 point to $x[0]$ and $x[N-1]$. AR1 and AR2 point to w and z array, respectively. IR0 contains value of $N/2 - 1$. The same instruction codes of weight update of transversal filter can be used in symmetric transversal structure by changing the x array pointer to the z array pointer. Appendix B2 presents an example program. The total number of instructions needed is $2.5N+15$, which is less than that of the transversal structure.

Lattice Structure [6]

An alternative FIR filter realization is the lattice structure [26]. A discussion of the transversal filter with the LMS algorithm shows that the convergence rate of the transversal structure is restricted by the correlation of signal components; i.e., the eigenvalue spread, $\lambda_{\max}/\lambda_{\min}$. The lattice structure is a decorrelating transform based on a family of prediction error filters as illustrated in Figure 10. The recursive equations that describe the lattice predictor are

$$f_0(n) = b_0(n) = x(n) \quad (17a)$$

$$f_m(n) = f_{m-1}(n) - k_m(n)b_{m-1}(n-1), \quad 0 < m \leq M \quad (17b)$$

$$b_m(n) = b_{m-1}(n-1) - k_m(n)f_{m-1}(n), \quad 0 < m \leq M \quad (17c)$$

where $f_m(n)$ represents the forward prediction error, $b_m(n)$ represents the backward prediction error, $k_m(n)$ is the reflection coefficients, m is the stage index, and M is the number of cascaded stages. The lattice structure has the advantage of being order-recursive. This property allows adding or deleting of stages from the lattice without affecting the existing stages.

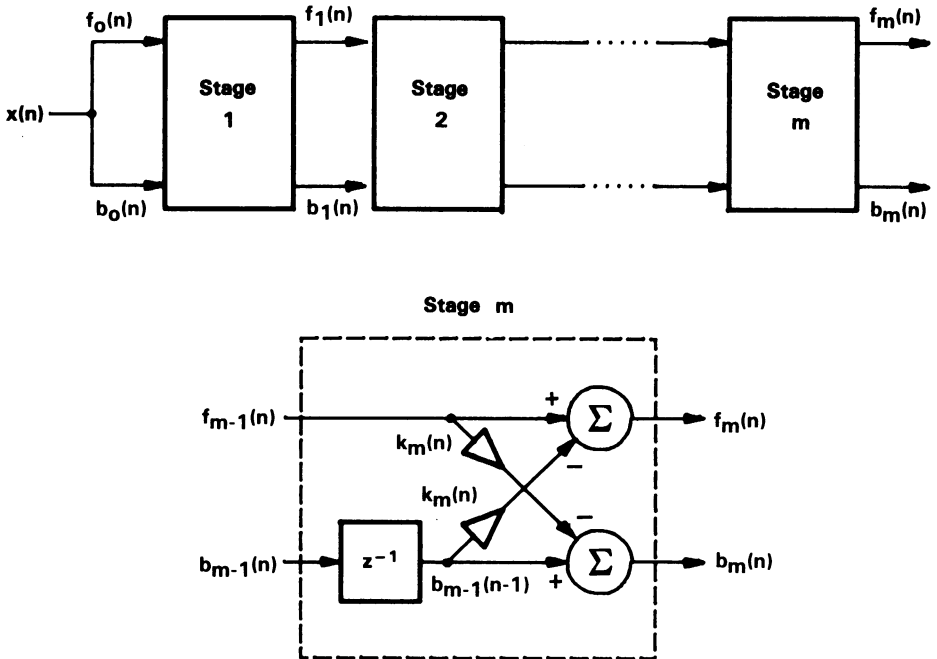


Figure 10. Lattice Structure

To implement the lattice filter for processing actual data, the reflection coefficients $k_m(n)$ are required. These coefficients can be computed according to estimates of the autocorrelation coefficients using Durbin's algorithm. However, it would be more efficient if these reflection coefficients could be estimated directly from the data and updated on a sample-by-sample basis, such as LMS algorithm [6]. The reflection coefficient $k_m(n+1)$ can be recursively computed [7]:

$$k_m(n+1) = k_m(n) + u[f_m(n)b_{m-1}(n-1) + b_m(n)f_{m-1}(n)], \quad 0 < m \leq M \quad (18)$$

For applications such as noise cancellation, channel equalization, line enhancement, etc., the joint-process estimation [3] illustrated in Figure 11 is required. This device performs two optimum estimations: the lattice predictor and the multiple regression filter. The following equations define the implementation of the regression filter

$$e_0(n) = d(n) - b_0(n)g_0(n) \quad (19a)$$

$$e_m(n) = e_{m-1}(n) - b_{m-1}(n)g_{m-1}(n), \quad 0 < m \leq M \quad (19b)$$

$$g_m(n+1) = g_m(n) + u_{em}(n)b_m(n), \quad 0 \leq m \leq M \quad (20)$$

where the LMS algorithm is used to update the coefficients of the regression filter. For noise cancellation application, $e_m(n)$ corresponds to the output $e(n)$ in Figure 5. For applications such as adaptive line enhancer and channel equalizer, filter output $y(n)$ is obtained as

$$y(n) = \sum_{m=0}^M g_m(n) b_m(n) \quad (21)$$

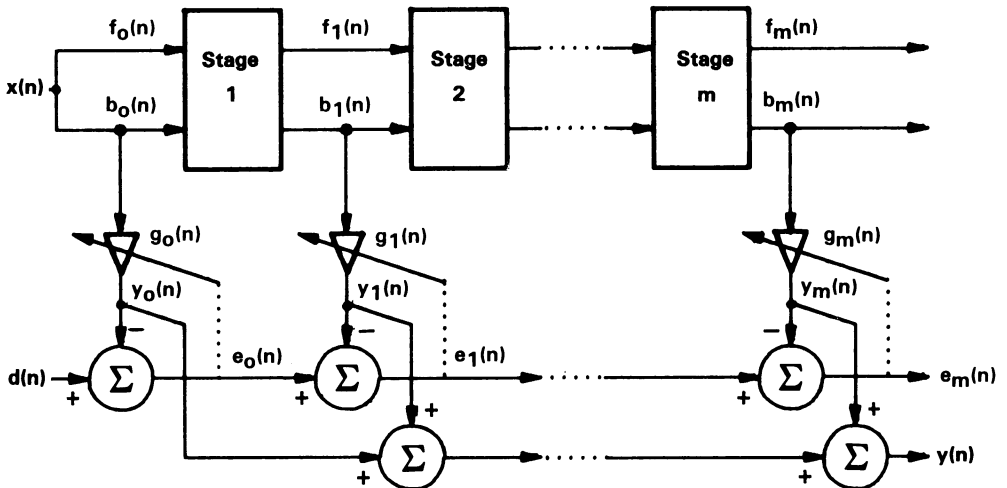


Figure 11. Lattice Structure with Joint Process Estimation

TMS320C25/TMS320C30 Implementation

There are five memory locations— $f_m(n)$, $b_m(n)$, $b_m(n-1)$, $k_m(n)$, and $g_m(n)$ —required for each stage. The limitation of on-chip data RAM is 544 words for the TMS320C25 and 2K words for the TMS320C30. A maximum of 102 stages can therefore be implemented on a single TMS320C25 for the highest throughput. Here, another advantage of TMS320C30 architecture design is shown. Since the operands of the mathematic operations can be either memory or register on the TMS320C30, and there is no need to preserve the values of f_m array for the next iteration (refer to Equations (17) and (18)), the f_m array can be replaced by an extended precision register. Thus, for the most efficient codes, the stage limitation of lattice structure for TMS320C30 is 512, or one-fourth of the 2K on-chip RAM.

Lattice structures have superior convergence properties relative to transversal structures and good stability properties; e.g., low sensitivity to coefficient quantization, low roundoff noise, and the ability to check stability by inspection. The disadvantages of lattice filter algorithms are that they are numerically complex and require mathematical sophistication to thoroughly understand their derivations. Furthermore, as shown in Appendixes C1 and C2, lattice structures cannot take advantage of the TMS320C25 and TMS320C30's pipeline architecture to achieve high throughput. The total number of instruction cycles needed is $33M+32$ for TMS320C25 and $14M+4$ for TMS320C30.

Modified LMS Algorithms [5]

The LMS algorithm described in previous sections is the most widely used algorithm in practical applications today. In this section, a set of LMS-type algorithms (all direct variants of the LMS algorithm) are presented and implemented. The motivation for each is some practical consideration, such as faster convergence, simplicity in implementation, or robustness in operation. The description of these algorithms is based on the transversal structure. However, these algorithms can be applied to the symmetric transversal structure and the lattice structure as well.

Normalized LMS Algorithm

The stability, convergence time, and fluctuation of the adaptation process is governed by the step size u and the input power to the adaptive filter. In some practical applications, you may need an automatic gain control (AGC) on the input to the adaptive filter. The normalized LMS algorithm is one important technique used to improve the speed of convergence. This is accomplished while maintaining the steady-state performance independent of the input signal power. This algorithm uses a variable convergence factor $u(n)$, which represents a u that is a function of the time index,

$$u(n) = a / \text{var}(n) \quad (22)$$

and

$$\underline{w}(n+1) = \underline{w}(n) + u(n)e(n)\underline{x}(n) \quad (23)$$

where a is a convergence parameter, and $\text{var}(n)$ is an estimate of the input average power at time n using the recursive equation

$$\text{var}(n) = (1 - b) \text{var}(n-1) + b x^2(n) \quad (24)$$

where $0 < b \ll 1$ is a smoothing parameter. In practice, a is chosen equal to b .

For fixed-point processors, there is a way to reduce the computation of power estimation. Since b in Equation (24) doesn't have to be an exact number, it is computationally convenient to make b a power of 2. If $b = 2^{-m}$, the multiplication of b can be implemented by shifting right m bits. Therefore, the $\text{var}(n)$ in Equation (24) is computed by

$$\begin{aligned} \text{var}(n) &= \text{var}(n-1) - b \text{var}(n-1) + b x^2(n) \\ &= \text{var}(n-1) - \text{var}(n-1) * 2^{-m} + x^2(n) * 2^{-m} \end{aligned}$$

Then, assuming the variance $\text{var}(n)$ of input signal is stored in the data memory VAR and its initial value is 0.99997 ($= 1 - 2^{-15}$), The implementation of this equation using TMS320C25 assembly code is

```
LARP   AR3
LRLK   AR3,FRSTAP   ; Point to input signal x
SQRA   *             ; Square input signal
SPH    ERRF
ZALH   VAR           ; ACC = var(n-1)
SUB    VAR,SHIFT    ; ACC = (1-b) var(n-1)
ADD    ERRF,SHIFT   ; ACC = (1-b) var(n-1) + b x^2(n)
SACH   VAR           ; Store var(n)
```

The normalized LMS algorithm can be implemented as

```
var = b1 * var + b * xn[0] * xn[0];
unen = e[n] * a / var;
for (i = 0; i < N; i++)
  wn[i] += unen * xn[i];
```

where $b_1 = (1-b)$, $xn[0] = x(n)$, and $unen = u(n)*e(n)$. This normalized technique reduces the dependency of convergence speed on input signal power at the cost of increased computational complexity, especially the division in Equation (22). The algorithms of implementing the fixed-point and floating-point division on the TMS320C25 and

TMS320C30 can be found in the user's guide for each device [13, 14]. Since the power of input signal is always positive, those codes can be simplified to save computation time.

Since the power estimation in Equation (24) and step size normalization in Equation (22) are performed once for each sample $x(n)$, the computation increase can be ignored when N is large. As shown in Appendixes D1 and D2, the total number of instruction cycles needed for the normalized LMS algorithm ($7N+57$ for the TMS320C25 and $3N+47$ for the TMS320C30) is slightly higher than for the LMS algorithm ($7N+34$ and $3N+15$) when N is large.

Sign LMS Algorithms

The LMS algorithm requires $2N$ multiplications and additions for each iteration; this amount is much lower than the requirements for many other complicated adaptive algorithms, such as Kalman and Recursive Least Square (RLS) [3]. However, there are three simplified versions of the LMS algorithm (sign-error LMS, sign-data LMS, and sign-sign LMS) that save the number of multiplications required and extend the real-time bandwidth for some applications [5, 27].

First, the sign-error LMS algorithm can be expressed as

$$\underline{w}(n+1) = \underline{w}(n) + u \operatorname{sign}[e(n)] \underline{x}(n) \quad (25)$$

$$\text{where} \quad \operatorname{sign}[e(n)] = \begin{cases} 1, & \text{if } e(n) \geq 0 \\ -1, & \text{if } e(n) < 0 \end{cases}$$

The C program implementation of sign-error LMS algorithm is

```
tu = u;
if (e[n] < 0.) {
    tu = -u; }
for (i=0; i<N; i++) {
    wn[i] += tu * xn[i];
}
```

As shown in Appendixes E1 and E2, the instruction sequence to implement weight update with the sign-error LMS algorithm is identical to that with the LMS algorithm. The difference is that the sign-error LMS algorithm uses the $\operatorname{sign}[e(n)]*u$ instead of $e(n)*u$ before the update loop. Note that, for fixed-point processors, if u is chosen to be a power of two, the $u x(n)$ can be accomplished by shifting right the elements in $x(n)$. This algorithm keeps the same convergence direction as the LMS algorithm. Thus, the sign-error LMS algorithm should remain efficient, provided the variable gain $u(n)$ is matched to this change. However, the use of constant step size u to reduce computation comes at the expense of a slow convergence rate since smaller u is normally used for stability reasons.

The programs in Appendixes E1 and E2 implement a transversal filter with sign-error LMS algorithm in looped code. The total number of instruction cycles needed for this algorithm using the TMS320C25 is $7N+26$, which is slightly less than for the LMS algorithm's $7N+28$. Computing $u*e(n)$ takes 5 instruction cycles. The sign-error LMS algorithm determines the sign of the u by checking the sign of $e(n)$, which takes only 3 instruction cycles. The total number of instruction cycles needed for the sign-error LMS algorithm using the TMS320C30 is $3N+16$, which is slightly higher than for the LMS algorithm. This occurs because the TMS320C30 takes only one instruction cycle to compute $u*e(n)$ and two instruction cycles to determine the sign of the u .

Secondly, the sign-data LMS algorithm is

$$\underline{w}(n+1) = \underline{w}(n) + u e(n) \text{sign}[\underline{x}(n)] \quad (26)$$

This equation can be implemented as

$$\begin{aligned} w_i(n+1) &= w_i(n) + ue(n) , \text{ if } x(n-i) \geq 0 \\ &= w_i(n) - ue(n) , \text{ if } x(n-i) < 0 \end{aligned}$$

for $i=0,1,\dots,N-1$. Since the sign determination is required inside the adaptation loop to determine the sign of $x(n-i)$, slower throughput is expected. The total number of instruction cycles needed is $11N+26$ for the TMS320C25 and $5N+16$ for the TMS320C30.

Finally, the sign-sign LMS algorithm is

$$\underline{w}(n+1) = \underline{w}(n) + u \text{sign}[e(n)] \text{sign}[\underline{x}(n)] \quad (27)$$

which requires no multiplications at all and is used in the CCITT standard for ADPCM transmission. As we can see from the above equations, the number of multiplications is reduced. This simplified LMS algorithm looks promising and is designed for VLSI or discrete IC implementation to save multiplications.

The sign-sign LMS algorithm can be implemented as

```
for (i=0; i<N; i++) {
    if (e[n] >= 0.) {
        if (xn[i] >= 0.)
            wn[i] += u;
        else
            wn[i] -= u; }
    else {
        if (xn[i] >= 0.)
            wn[i] -= u; }
```

else

wn[i] += u; } }

When this algorithm is implemented on TMS320C25 and TMS320C30 with pipeline architecture and a parallel multiplier, the performance of sign-sign LMS algorithm is poor compared to standard LMS algorithm due to the determination of sign of data, which can break the instruction pipeline and can severely reduce the execution speed of the processors.

In order to avoid double branches inside the loop, the XOR instruction is utilized to check the sign bit of $e(n)$ and $x(n-i)$. The sign-sign LMS algorithm can be implemented as

$$\begin{aligned}w_i(n+1) &= w_i(n) + u, \text{ if } \text{sign}[e(n)] = \text{sign}[x(n-i)] \\ &= w_i(n) - u, \text{ otherwise}\end{aligned}$$

The following TMS320C25 instruction sequence implements this algorithm without branching (assuming that the current address register used is AR3):

	LRLK	AR1,N-1	; Set up counter
	LRLK	AR2,COEFFD	; Point to $w_i(n)$
	LRLK	AR3,LASTAP+1	; Point to $x(n-i)$
ADAP	LAC	*-,0,AR2	; Load $x(n-i)$
	XOR	ERR	; XOR with $e(n)$
	SACL	ERRF	; Save sign bit, sign = 0 if same signs ; Sign = 1 if different signs
	LAC	ERRF	; Sign extension to ACCH, ; ACCH = 0 If ERRF \geq 0 ; ACCH = 0FFFFh if ERRF $<$ 0
	XORK	MU,15	; Take one's complement of m ; If sign = 1
	ADD	*,15	; Weight update
	SACH	*+,1,AR1	; Save new weight
	BANZ	ADAP,*-,AR3	

The one's complement of u is used instead of $-u$, because they are only slightly different and the step size does not require the exact number. The weight update with this technique requires $10N$ instruction cycles and FIR filtering requires N instruction cycles so that the total number of instruction cycles needed is $11N+21$. The complete TMS320C25 assembly program is given in Appendix F1.

To determine whether a positive or negative u should be used without branching is trickier in the TMS320C30. Fortunately, the extended precision registers of TMS320C30 interpret the 32 most-significant bits of the 40-bit data as the floating-point number and the 32 least-significant bits of the 40-bit data as an integer. When a floating-point number

changes its sign, its exponent remains the same. Therefore, the sign of step size u can be determined by using XOR logic on its mantissa. The following code shows how the sign-sign LMS algorithm is implemented on the TMS320C30.

```

    ASH    -31,R7          ; R7 = Sign[e(n)]
    XOR3   R0,R7,R5       ; R5 = Sign[e(n)] * u
    LDF    *AR0++(1),R6   ; R6 = x(n)
    ASH    -31,R6         ; R6 = Sign[x(n-i)]
    XOR3   R5,R6,R4       ; R4 = Sign[x(n-i)]*Sign[e(n)] * u
    ADDF3  *AR1,R4,R3     ; R3 = wi(n) + R4

    LDI    order-3,RC     ; Initialize repeat counter
    RPTB   SSLMS         ; Do i = 0, N-3
    LDF    *AR0++(1),R6   ; Get next data
    | |   STF    R3,*AR1++(1)% ; Update wi(n+1)
    ASH    -31,R6         ; Get the sign of data
    XOR3   R5,R6,R4       ; Decide the sign of u
    SSLMS  ADDF3  *AR1,R4,R3 ; R3 = wi(n) + R4

    LDF    *AR0,R6        ; Get last data
    | |   STF    R3,*AR1++(1)% ; Update wN-2(n+1)
    ASH    -31,R6         ; Get the sign of data
    XOR3   R5,R6,R4       ; Decide the sign of u
    ADDF3  *AR1,R4,R3     ; Compute wN-1(n+1)
    STF    R3,*AR1++(1)% ; Store last w(n+1)

```

Here, R0, R4, and R5 contain the value of u before updating. AR0 and AR1 point to x array and w array, respectively. R7 contains the value of error signal $e(n)$. The complete program is given in Appendix F2. The total number of instruction cycles is $5N + 16$, which is much higher than LMS algorithm.

The sign-sign LMS algorithm is developed to reduce the multiplication requirement of the LMS algorithm. Since DSPs provide the hardware multiplier as a standard feature, this modification does not provide any advantage when implementing this algorithm on the DSPs. On the contrary, it causes some disadvantages since decision instructions will destroy the instruction pipeline. If you use the XOR logic operation in order to avoid using the decision instructions, the complexity of the program will be increased and the total number of instruction cycles will be greater than the regular LMS algorithm.

Leaky LMS Algorithm

When adaptive filters are implemented on signal processors with fixed word lengths, roundoff noise is fed back to adaptive weights and accumulates in time without bound. This leads to an overflow that is unacceptable for real-time applications. One solution is

based upon adding a small forcing function, which tends to bias each filter weight toward zero. The leaky LMS algorithm has the form

$$\underline{w}(n+1) = r \underline{w}(n) + u e(n) \underline{x}(n) \quad (28a)$$

where r is slightly less than 1.

Since r can be expressed as $1 - c$ and $c \ll 1$, the TMS320C25 can take advantage of the built-in shifters to implement this algorithm. Therefore, Equation (28a) can be changed to

$$\underline{w}(n+1) = \underline{w}(n) - c \underline{w}(n) + u e(n) \underline{x}(n) \quad (28b)$$

In order to achieve the highest throughput by using ZALR and MPYA, $cw(n)$ can be implemented by shifting $w_i(n)$ right by m bits where 2^{-m} is close to c . Since the length of the accumulator is 32 bits and the high word (bits 16 to 31) is used for updating $w(n)$, shifting right m bits of $w_i(n)$ can be implemented by loading $w_i(n)$ and shifting left $16 - m$ bits. The sequence of TMS320C25 instructions to implement Equation (28b) is shown as

	LRLK	AR1,N-1	; Set up counter
	LRLK	AR2,COEFFD	; Point to $w_i(n)$
	LRLK	AR3,LASTAP+1	; Point to $x(n - i)$
	LT	ERRF	; $T = \text{ERRF} = u * e(n)$
	MPY	*-,AR2	
ADAPT	ZALR	*,AR3	
	MPYA	*-,AR2	
	SUB	*,LEAKY	; $\text{LEAKY} = 16 - m$
	SACH	*+,0,AR1	
	BANZ	ADAPT,*-,AR2	

For each iteration, 7N instruction cycles are needed to perform the adaptation process (6N for the LMS algorithm). The total number of instruction cycles needed is $8N + 28$ (see Appendix G1 for the complete program). The leaky factor r has the same effect as adding a white noise to the input. This technique not only can solve adaptive weights overflow problem, but also can be beneficial in an insufficient spectral excitation and stalling situation [5].

The method used above is especially for the TMS320C25, which has a free shift feature. Since TMS320C30 is a floating-point processor, r can simply multiply to filter coefficient. However, in order to reduce the instruction cycles, this multiplication can combine with another instruction to be a parallel instruction inside the loop. The following code shows how to rearrange the instructions from the LMS algorithm to include this multiplication without an extra instruction cycle.

```

MPYF  @u_r,R7          ; R7 = e(n)*u/r
MPYF3 *AR0++(1)%,R7,R1 ; R1 = e(n)*u*x(n)/r
MPYF3 *AR0++(1)%,R7,R1 ; R1 = e(n)*u*x(n-1)/r
| | ADDF3 *AR1,R1,R2    ; R2 = w0(n) + e(n)*u*x(n)/r
  LDI  order-4,RC      ; Initialize repeat counter
  RPTB LLMS           ; do i = 0, N-4
  MPYF3 *AR2,R2,R0     ; R0 = r*wi(n) + e(n)*u*x(n-i)
| | ADDF3 *+AR1(1),R1,R2 ; R2 = wi+1(n) + e(n)*u*x(nz-i-1)/r
LLMS  MPYF3 *AR0++(1)%,R7,R1 ; R1 = e(n)*u*x(n-i-2)/r
| | STF  R0,*AR1++(1)%  ; Store wi(n+1)

MPYF3 *AR2,R2,R0     ; R0 = r*wN-3(n) + e(n)*u*x(n-N+3)
| | ADDF3 *+AR1(1),R1,R2 ; R2 = wN-2(n) + e(n)*u*x(n-N+2)/r
  MPYF3 *AR0,R7,R1    ; R1 = e(n)*u*x(n-N+1)/r
| | STF  R0,*AR1++(1)%  ; Store wN-3(n+1)
  MPYF3 *AR2,R2,R0     ; R0 = r*wi(n) + e(n)*u*x(n-N+2)
| | ADDF3 *+AR1(1),R1,R2 ; R2 = wN-1(n) +
*                                     e(n)*u*x(n-N+1)/r
  MPYF3 *AR2,R2,R0     ; R0 = r*wi(n) + e(n)*u*x(n-N+1)
| | STF  R0,*AR1++(1)%  ; Store wN-2(n+1)
  STF  R0,*AR1++(1)%  ; Update last w

```

Auxiliary registers AR0 and AR1 point to x and w arrays. AR2 points to the memory location that contains value r. R7 contains the value of error signal e(n). R1 and R2 are updated before the loop because the parallel instructions inside the loop use the previous values in R1 and R2. Note that R1 is updated twice before the loop because the updating of R2 requires the previous value of R1. In order to update x array pointer to the new beginning of the data buffer for next iteration, two of the loop instruction sets have been taken out of loop and modified by eliminating the incrementation of AR0. The TMS320C30 assembly program of an adaptive transversal filter with the leakage LMS algorithm is listed in Appendix G2 as an example. The total number of instruction cycles for this algorithm is $3N+15$, which is the same as the LMS algorithm. This example shows the power and flexibility of the TMS320C30.

Implementation Considerations

The adaptive filter structures and algorithms discussed previously were derived on the basis of infinite precision arithmetic. When implementing these structures and algorithms on a fixed integer machine, there is a limitation on the accuracy of these filters due to the fact that the DSP operates with a finite number of bits. Thus, designers must pay attention to the effects of finite word length. In general, these effects are input quantization, roundoff in the arithmetic operation, dynamic range constraints, and quantization of filter coefficients. These effects can either cause deviations from the original design criteria or create an effective noise at the filter output. These problems have been investigated extensively, and techniques to solve these problems have been developed [28, 29].

The effects of finite precision in adaptive filters is an active research area, and some significant results have been reported [30 through 32]. There are three categories of finite word length effects in adaptive filters:

- Dynamic Range Constraint (scaling to avoid overflow). Since this is not applicable for a floating-point processor, the TMS320C30 is not mentioned in this portion.
- Finite Precision Errors (errors introduced by roundoff in the arithmetic).
- Design Issues (design of the optimum step size u that minimizes system noise).

Dynamic Range Constraint

As shown in Figure 1, the most widely used LMS transversal filter is specified by the difference equations

$$y(n) = \sum_{i=0}^{N-1} w_i(n) x(n-i) \quad (29)$$

and

$$w_i(n+1) = w_i(n) + u * e(n) * x(n-i), \text{ for } i = 0, 1, \dots, N-1 \quad (30)$$

where $x(n-i)$ is the input sequence and $w_i(n)$ are the filter coefficients.

If the input sequence and filter coefficients are properly normalized so that their values lie between -1 and 1 using Q15 format, no error is introduced into the addition. However, the sum of two numbers may become larger than one. This is known as overflow. The TMS320C25 provides four features that can be applied to handle overflow management [13]:

- A. Branch on overflow conditions.
- B. Overflow mode (saturation arithmetic).
- C. Product register right shift.
- D. Accumulator right shift.

One technique to inhibit the probability of overflow is scaling, i.e., constraining each node within an adaptive filter to maintain a magnitude less than unity. In Equation (29), the condition for $|y(n)| < 1$ is

$$x_{\max} < 1 / \sum_{i=0}^{N-1} |w_i(n)| \tag{31}$$

where x_{\max} denotes the maximum of the absolute value of the input. The right shifter of the TMS320C25, which operates with no cycle overhead, can be applied to implement scaling to prevent overflow of multiply-accumulate operations in Equation (29). By setting the PM bits of status register ST1 to 11 using the SPM or LST1 instructions, the P register output is right-shifted 6 places. This allows up to 128 accumulations without the possibility of an overflow. SFR instruction can also be used to right shift one bit of the accumulator when it is near overflow.

Another effective technique to prevent overflow in the computation of Equation (29) is using saturation arithmetic. As illustrated in Figure 12, if the result of an addition overflows, the output is clamped at the maximum value. If saturation arithmetic is used, it is common practice [28] to permit the amplitude of $x(n-i)$ to be larger than the upper bound given in Equation (31). Saturation of the filter represents a distortion, and the choice of scaling on the input depends on how often such distortion is permissible. The saturation arithmetic on the TMS320C25 is controlled by the OVM bit of status register ST0 and can be changed by the SOVM (set overflow mode), ROVM (reset overflow mode), or LST (load status register).

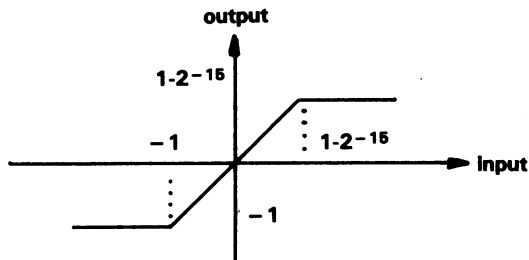


Figure 12. Saturation Arithmetic

Filter coefficients are updated using Equation (30). As illustrated in Figure 13, a new technique presented in reference 31 uses the scaling factor a to prevent filter's coefficients overflow during the weight updating operation. Suppose you use $a = 2^{-m}$. A right shift by m bits implements multiplication by a , while a left shift by m bits implements the scaling factor $1/a$. Usually, the required value of a is not expected to be very small and depends on the application. Since a scales the desired signal, it does not affect the rate of convergence.

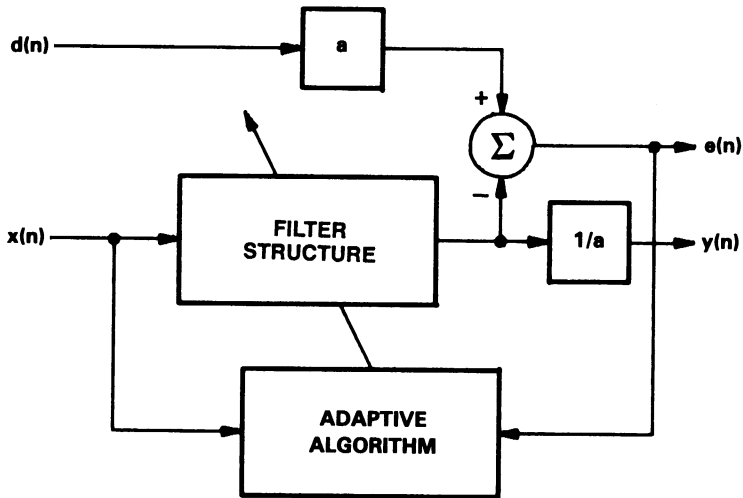


Figure 13. Fixed-Point Arithmetic Model of the Adaptive Filter

Finite Precision Errors

The TMS320C25 is a 16/32-bit fixed point processor. Each data sample is represented by a fractional number that uses 15 magnitude bits and one sign bit. The quantization interval

$$\delta = 2^{-b}, \quad (32)$$

($b = 15$), is called the width of quantization since the numbers are quantized in steps of δ .

The products of the multiplications of data by coefficients within the filter must be rounded or truncated to store in memory or a CPU register. As shown in Figure 14, the roundoff error can be modeled as the white noise injected into the filter by each rounding operation. This white noise has a uniform distribution over a quantization interval and for rounding

$$- 1/2 \delta < e \leq 1/2 \delta \quad (33a)$$

and

$$\delta_e^2 = (1/12) \delta^2 \quad (33b)$$

where δ_e^2 is the variance of the white noise.

In general, roundoff noise occurs after each multiplication. However, the TMS320C25 has a full precision accumulator, i.e., a 16×16 -bit multiplier with a 32-bit accumulator, so there is no roundoff when you implement a set of summations and multiplications as in Equation (29). Rounding is performed when the result is stored back to memory location $y(n)$, so that only one noise source is presented in a given summation node.

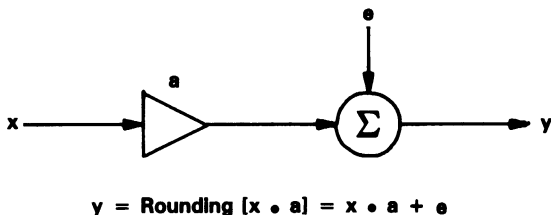


Figure 14. Fixed-Point Roundoff Noise Model

For floating-point arithmetic, the variance of the roundoff noise [31] is slightly different from Equation (33b),

$$\sigma_e^2 = 0.18 \delta^2 \quad (33c)$$

Since TMS320C30 has a 40/32-bit floating-point multiplier and ALU, the result from arithmetic operation has the mantissa of [31] bits plus one sign bit. Therefore, the δ in Equation (33c) is equal to 2^{-31} . Another roundoff noise is introduced when you restore the result back to memory. This noise has the power of 2^{-23} because the mantissa of TMS320C30 floating-point data is 23 bits plus one sign bit. Therefore, unless the filter order is high, the roundoff noise from arithmetic operation is relatively small.

The steady-state output error of the LMS algorithm due to the finite precision arithmetic of a digital processor was analyzed in reference [31]. It was found that the power of arithmetic errors is inversely proportional to the adaptation step size u . The significance of this result in the adaptive filter design is discussed next. Furthermore, roundoff noise is found to accumulate in time without bound, leading to an eventual overflow [32]. The leaky LMS algorithm presented in the previous section can be used to prevent the algorithm overflow.

Design Issues

The performance of digital adaptive algorithms differs from infinite precision adaptive algorithms. The finite precision LMS algorithm is given as

$$\underline{w}(n+1) = \underline{w}(n) + Q[u * e(n) * \underline{x}(n)] \quad (34)$$

where $Q[\cdot]$ denotes the operation of fixed point quantization. Whenever any correction term $u * e(n) * x(n-i)$ in the update of the weight vector in Equation (34) is too small, the quantized value of that term is zero, and the corresponding weight $w_i(n)$ remains unchanged. The condition for the i th component of the vector $w(n)$ not to be updated when the algorithm is implemented with the TMS320C25 is

$$| u e(n) x(n-i) | < \delta/2 \quad (35a)$$

where $\delta = 2^{-15}$. The condition for TMS320C30 is

$$| u e(n) x(n-i) | < 2^{\text{exp}} * \delta/2 \quad (35b)$$

where exp is the exponent of $w_i(n)$ and $\delta = 2^{-23}$.

Since the adaptive algorithms are designed to minimize the mean squared value of the error signal, $e(n)$ decreases with time. If u is small enough, most of the time the weights are not updated. This early termination of the adaptation may not allow the weight values to converge to the optimum set, resulting in a mean square error larger than its minimum value. The conditions for the adaptation to converge completely [30] is $u > u_{\min}$ where

$$u_{\min}^2 = \frac{\delta^2}{4\sigma_x^2 \epsilon_{\min}} \quad (36a)$$

for the TMS320C25 and the TMS320C30

$$u_{\min}^2 = \frac{\delta^2 * 2^{\text{exp}}}{4\sigma_x^2 \epsilon_{\min}} \quad (36b)$$

where σ_x^2 is the power of input signal $x(n)$ and ϵ_{\min} is the minimum mean squared error at steady state.

In the Leaky LMS Algorithm section, it was mentioned that the excess MSE given in Equation (14) is minimized by using small u . However, this may result in a large quantization error since the most significant term in the total output quantization error is [31]

$$\frac{N\sigma_e^2}{2a^2u} \quad (37)$$

The optimum step size u_0 reflects a compromise between these conflicting goals. The value of u_0 is shown to be too small to allow the adaptive algorithm to converge completely and also to give a slow convergence. In practice, $u > u_0$ is used for faster convergence. Hence, the excess MSE becomes larger, and the roundoff noise can typically be neglected when compared with the excess mean square error.

Finally, recall Equations (11) and (12). The step size u has an upper limit to guarantee the stability and convergence. Therefore, the adaptive algorithm requires

$$0 < u < \frac{1}{N\sigma_x^2} \quad (38)$$

On the other hand, the step size u also has a lower limit. The optimum u_0 , which minimizes the sum of the excess MSE and roundoff noise, is smaller than u_{\min} , i.e., too small to allow the adaptive weight to converge. For an algorithm implemented on the TMS320C25, the word-length of 16 bits is fixed, and the minimum step-size that can be used is given in Equation (36). The most important design issue is to find the best u to satisfy

$$u_{\min} < u < \frac{1}{N\sigma_x^2} \quad (39)$$

Therefore, in order to make the condition in Equation (39) valid, the initial values of filter coefficients are better close to zero for the floating-point processor if the situation is unknown.

Software Development

The TMS320C25 and TMS320C30 combine the high performance and the special features needed in adaptive signal processing applications. The processors are supported by a full set of software and hardware development tools. The software development tools include an assembler, a linker, a simulator, and a C compiler. The most universal software development tool available is a macro assembler. However, the assembly language programming for DSP can be tedious and costly. For adaptive filter applications, an assembly language programmer must have knowledge of adaptive signal processing. The challenge lies in compressing a great deal of complex code into the fairly small space and most efficient code dictated by the real-time applications typical of adaptive signal processing.

Recently, C compilers for the processors were developed to make DSP programming easier, quicker, and less costly compared with the work associated with programming in assembly language. Due to the general characteristics of a compiler, the code it generates is not the most efficient. Since the program efficiency consideration is important for adaptive filter implementation, the code generated from the C compiler has to be modified before implementing. Thus, two alternative ways, besides writing an assembly program, to implement adaptive signal processing on DSP are presented. First is the automatic adaptive filter code generator [12], which can be found on Texas Instruments TMS320 Bulletin Board Service (BBS), and second are the adaptive filter function libraries that support assembly and C programming languages.

In this report, two adaptive filter libraries have been developed: one can be called from an assembly main program; the other can be called from the C main program. Note that, for the TMS320C25 only, certain data memory locations have been reserved for storing the necessary filter coefficients, previous delayed signal, etc. In other words, these data memories are used as global variables.

Assembly Function Libraries

The basic concept of creating an assembly subroutine for an adaptive filter is to modify in module the assembly programs discussed above. Then, the user can implement the adaptive filter by writing his own assembly main program that calls the subroutine.

TMS320C25 Assembly Subroutine

The TMS320C25 has an eight-level deep hardware stack. The CALL and CALA subroutine calls store the current contents of the program counter (PC) on the top of the stack. The RET (return from subroutine) instruction pops the top of the stack back to the PC. For computational convenience, the processor needs to be set as follows before calling the assembly callable subroutine.

1. PM status bits equal to 01.
2. SXM status bit set to 1.
3. The current DP (data memory page pointer) is 0.

The following example is the TMS320C25 assembly main routine, which performs an adaptive line enhancement by calling the LMS algorithm subroutine. The filter order is 64, delay is equal to one, and the convergence factor u is 0.01.

```
*   DEFINE AND REFER SYMBOLS
*
      .global ORDER,U,ONE,D,Y,ERR,XN,WN,LMS
*
```

DEFINE SAMPLING RATE, ORDER, AND MU

*

ORDER: .equ 20
 MU: .equ 327 ; mu = 0.01 in Q15 format
 PAGE0: .equ 0

*

DEFINE ADDRESSES OF BUFFER AND COEFFICIENTS

*

X0: .usect "buffer",ORDER-1
 XN: .usect "buffer",1
 WN: .usect "coeffs",ORDER

*

RESERVE ADDRESSES FOR PARAMETERS

*

ONE: .usect "parameters",1
 U: .usect "parameters",1
 ERR: .usect "parameters",1
 Y: .usect "parameters",1
 D: .usect "parameters",1
 ERRF: .usect "parameters",1

*

INITIALIZATION

*

START LDPK PAGE0 ; Set DP = 0
 SPM 1 ; Set PM equal to 1
 SSSXM ; Set sign extension mode
 LRLK AR7,X0 ; AR7 point to >300
 LACK 1 ; Initialize ONE = 1
 SACL ONE
 LALK MU ; Initialize U = MU = 0.01
 SACL U

PERFORM THE PREDICTOR

INPUT: IN D,PA2 ; Get the input
 *
 CALL LMS ; Call subroutine

*

OUTPUT: OUT Y,PA2 ; Output the signal
 *
 LAC D ; Insert the newest sample
 LARP AR7
 SACL *
 B INPUT
 .end

The symbols, such as ORDER, U, ONE, D, LMS, Y, and ERR, are defined and referred to for the purpose of modular programming. The uninitialized sections specified by the directive .usect can be placed in any location of memory according to the linker command file. Note that MACD instruction requires the sources of the operands on program memory and data memory separately, and CNFP instruction configures RAM block 0 as program memory. Therefore, the coeffs section has to be in data RAM block 0, and the buffer has to be in RAM block 1. Appendix H1 contains the adaptive transversal filter with LMS algorithm subroutine using the TMS320C25, and Appendix H2 contains an example of a linker command file.

TMS320C30 Assembly Subroutine

Instead of a hardware stack, TMS320C30 uses a software stack, which is more flexible and convenient for a high-level language compiler. The stack memory location is pointed to by the stack pointer SP. In order to maintain the proper program sequence, the programmer must make certain that no data is lost and that the stack pointer always points to proper location. The PUSH, PUSHF, POP, POPF, CALL, CALLcond, RETIcond, and RETScond instructions will change the value of the stack pointer; in addition, writing data into it and using the interrupt will also change that value. It is the programmer's responsibility to initialize the stack pointer in the beginning of the program. The same adaptive line enhancer example above using TMS320C30 is listed below. The adapfltr.int program that initializes the stack pointer and the data RAM is given in Appendix H3.

```

*
*   DEFINE GLOBAL VARIABLES AND CONSTANTS
*
        .copy    "adapfltr.int"
        .global  LMS30,order,u,d,y,e
N      .set     20
mu     .set     0.01
*
*   INITIALIZE POINTERS AND ARRAYS
*
        .text
begin  .set     $
        LDI     N,BK           ; Set up circular buffer
        LDP     @xn__addr     ; Set data page
        LDI     @xn__addr,AR0 ; Set pointer for x[]
        LDI     @wn__addr,AR1 ; Set pointer for w[]
        LDF     0.0,R0        ; R0 = 0.0
        RPTS   N-1
        STF     R0,*AR0++(1)% ; x[] = 0.

```

```

| |STF    R0,*AR1++(1)% ; w[] = 0.
  LDI    @in__addr,AR6  ; Set pointer for input ports
  LDI    @out__addr,AR7 ; Set pointer for output ports

```

*

*

PERFORM ADAPTIVE LINE ENHANCER

*

input:

```

  LDF    *AR6,R7          ; Input d(n)
| |LDF    *+AR6(1),R6     ; Input x(n)
  STF    R7,@d           ; Insert d(n)
  STF    R6,*AR0         ; Insert x(n) to buffer

```

*

*

CALL ASSEMBLY SUBROUTINE

*

*

CALL LMS30

*

OUTPUT y(n) AND e(n) SIGNALS

*

```

  LDF    @y,R6           ; Get y(n)
  BD     input           ; Delay branch
  LDF    @e,R7           ; Get e(n)
  STF    R6,*AR7        ; Send out y(n)
  STF    R7,*+AR7(1)    ; Send out e(n)

```

*

*

DEFINE CONSTANTS

*

```

n          .usect  "buffer",N
wn         .usect  "coeffs",N
in__addr  .usect  "vars",1
out__addr .usect  "vars",1
xn__addr  .usect  "vars",1
wn__addr  .usect  "vars",1
u          .usect  "vars",1
order     .usect  "vars",1
d         .usect  "vars",1
y         .usect  "vars",1
e         .usect  "vars",1
cinit     .sect   ".cinit"
          .word   6,in__addr
          .word   0804000h
          .word   0804002h
          .word   xn
          .word   wn

```

```
.float    mu
.word    N-2
.end
```

In the above example, data memory order is initialized to $N-2$ for computation convenience. The linker command files and the subroutine that implements the LMS transversal filter can be found in Appendixes H4 and H5.

C Function Libraries

The TMS320C25 and TMS320C30 C language compilers provide high-level language support for these processors. The compilers allow application developers without an extensive knowledge of the device's architecture and instruction set to generate assembly code for the device. Also, since C programs are not device-specific, it is a relatively straightforward task to port existing C programs from other systems.

To allow fast development of efficient programs for adaptive signal processing applications, C function libraries have been developed. These libraries include functions for adaptive transversal, symmetric transversal, and lattice structures.

TMS320C25 C-Callable Subroutines

In a C program, the memory assignments are chosen by the compiler. There are two ways to use the most efficient instruction MACD:

- A. Use inline assembly code to assign memory locations for filter coefficients and buffers.
- B. Reserve the desired memory locations for them and do the assignment in the linker command file.

The latter method is used in this report.

For a C main program, the parameters passed to and returned from the subroutines are all within the parentheses following the subroutine name, as shown below:

```
lms(n,mu,d,x,&y,&e)    n - Filter order
                      mu - Convergence factor
                      d - Desired signal
                      x - Input signal
                      y - Address of output signal
                      e - Address of error signal
```

Since the TMS320C25 C compiler pushes the parameters from right to left into software stack pointed by AR1, the subroutine gets the parameters in reverse order, as shown below:

```
MAR    * -           ; Set pointer for getting parameters
LAC    * -           ; ACC = N
```



```

SUBK    1
SACL   ORDER      ; ORDER = N - 1
LAC    *--        ; Getting and storing the mu
SACL   U
LAC    *--        ; Getting and storing the D
SACL   D
LAC    *-,0,A-R3  ; Insert the newest sample
LRLK   AR3,FRSTAP
SACL   *

```

The assembly subroutine returns the parameters y and e as follows:

```

LARP   AR1
LAR    AR2,*--,AR2 ; Get the address of y in main
LAC    Y
SACL   *,0,AR1     ; Store y
LAR    AR2,*-,AR2  ; Get the address of e in main
LAC    ERR
SACL   *,0,AR1     ; Store e

```

Therefore, the parameters should be entered in the order given above. If there are other parameters, they should be inserted right after the convergence factor μ . The leaky LMS algorithm subroutine is given as an example.

$llms(n, \mu, r, d, x, \&y, \&e)$

the r is defined in Equation (28a). Note that the values of the AR registers, which will be used in subroutine, and the status registers must be saved at the beginning of the subroutine and restored right before returning to calling routine. An example of a C-callable program is given in Appendix II. Memory locations $0200h$ to $0200h + N - 1$ and $0300h$ to $0300h + N - 1$ are reserved for filter coefficients and buffers, respectively. N denotes the filter order.

TMS320C30 C Subroutine

As previously mentioned, the TMS320C30 architecture has features designed for a high-level language compiler. Note that the callable word is dropped in this section title because the TMS320C30 is so flexible that the restrictions for the TMS320C25 no longer exist. Since the memory locations of filter buffers and coefficients are determined by the parameters that pass from the calling routine, the same subroutine can be used in different places. However, the only restriction is that the memory locations of filter buffers must align to the circular addressing boundary [14]. The features of TMS320C30 architecture that make a major contribution toward these improvements are dual data address buses, software stack, and flexible addressing mode. The parameters passed to subroutine are pushed into the stack. Therefore, after returning from the subroutine, the stack pointer, SP, must be updated to point to the location where SP pointed before pushing the parameters

into the stack. However, this will be done by the C compiler. The usage example of the C function subroutine is given as follows:

tlms(n,u,d,&w,&x,&y,&e) where

- n - Filter order
- u - Step size
- d - Desired signal
- &w - Filter coefficients
- &x - Input signal buffers
- &y - Addr of output signal
- &e - Addr of error signal

The example below shows how the C subroutine receives and manipulates the parameters passed from the caller program and how the result is returned to the caller routine.

```

*
*   SET FRAME POINTER FP
*
FP   .set    AR3
      PUSH   FP
      LDI    SP,FP
*
*   GET FILTER PARAMETERS
*
      LDI    *-FP(2),R4    ; Get filter order
      LDI    *-FP(6),AR0   ; Get pointer for x[]
      LDI    *-FP(5),AR1   ; Get pointer for w[]
*
*   COMPUTE ERROR SIGNAL e(n) AND STORE y(n) AND e(n)
*
      LDI    *-FP(2),AR2   ; Get y(n) address
      SUBF3  R2,*+FP(1),R7 ; e(n) = d(n) - y(n)
|     STF    R2,*AR2       ; Send out y(n)
      LDI    *-FP(3),AR2   ; Get e(n) address
      STF    R7,*AR2       ; Send out e(n)
      MPYF   *+FP(2),R7    ; R7 = e(n) * u
      POP    FP

```

Note that AR3 is used as the frame pointer in TMS320C30 C compiler. Appendix I2 contains the complete LMS transversal filter example subroutine program.

Development Process and Environment

Following a four stage procedure [33] to minimize the amount of finite word length effect analysis and real-time debugging, adaptive structures and algorithms are implemented

on the TMS320C25. Figure 15 illustrates the flowchart of this procedure. Since the implementation on TMS320C30 is done only by the simulator, the last stage, real-time testing, is not implemented.

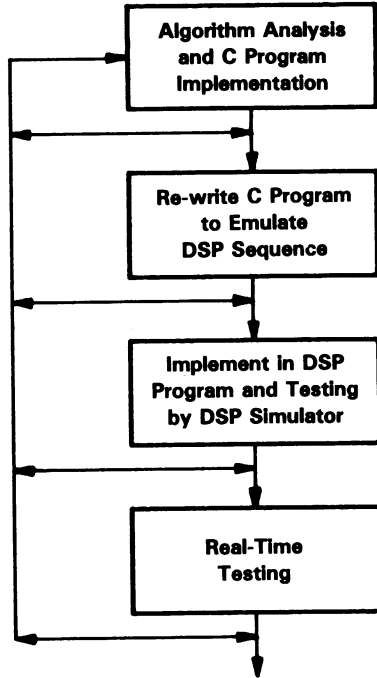


Figure 15. Adaptive Filter Implementation Procedure

In the first stage, algorithm design and study is performed on a personal computer. Once the algorithm is understood, the filter is implemented using a high-level C program with double precision coefficients and arithmetic. This filter is considered an ideal filter.

In the second stage, the C program is rewritten in a way that emulates the same sequence of operations with the same parameters and state variables that will be implemented in the processors. This program then serves as a detailed outline for the DSP assembly language program or can be compiled using TMS320C25 or TMS320C30 C compiler. The effects of numerical errors can be measured directly by means of the technique shown in Figure 16, where $H(z)$ is the ideal filter implemented in the first stage and $H'(z)$ is a real filter. Optimization is performed to minimize the quantization error and produce stable implementation.

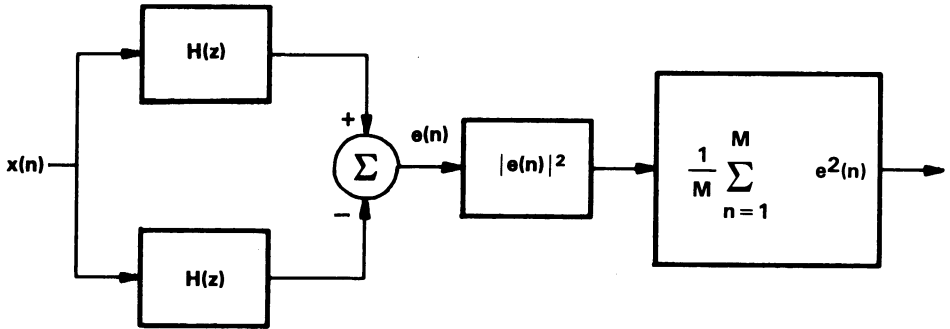


Figure 16. A Commutational Technique for Evaluating Quantization Effects

In the third stage, the TMS320C25 and TMS320C30 assembly programs are developed; then they are tested using the simulators with test data from a disk file. Note that the simulation of TMS320C25 can also be implemented on the SWDS with the data logging option. This test data is a short version of the data used in stage 2 that can be internally generated from a program or data digitized from a real application environment. Output from the simulation is compared against the equivalent output of the C program in the second stage. Since the simulation requires data files to be in Q15 format, certain precision is lost during data conversion. When a one-to-one agreement within tolerable range is obtained between these two outputs, the processor software is assured to be essentially correct.

The final stage is applied only to the TMS320C25. First, you download this assembled program into the target TMS320C25 system (SWDS) to initiate real-time operation. Thus, the real-time debugging process is constrained primarily to debugging the I/O timing structure of the algorithm and testing the long-term stability of the algorithm. Figure 17 shows an experimental setup for verification, in which the adaptive filter is configured for a one-step adaptive predictor illustrated in Figure 18. The data used for real-time testing is a sinusoid generated by a Tektronix FG504 Function Generator embedded in white noise generated by an HP Precision Noise Generator. The DSP gets a quantized signal from the Analog Interface Board (AIB), performs adaptive prediction routines, and outputs an enhanced sinusoid to the analog interface board. The corrupted input and predicted (enhanced) output waveforms are compared on the oscilloscope or on the HP 4361 Dynamic Signal Analyzer. The corresponding spectra of input and output can be compared on the signal analyzer. The signal-to-noise ratio (SNR) improvement can be measured from the analyzer, which is connected to an HP plotter.

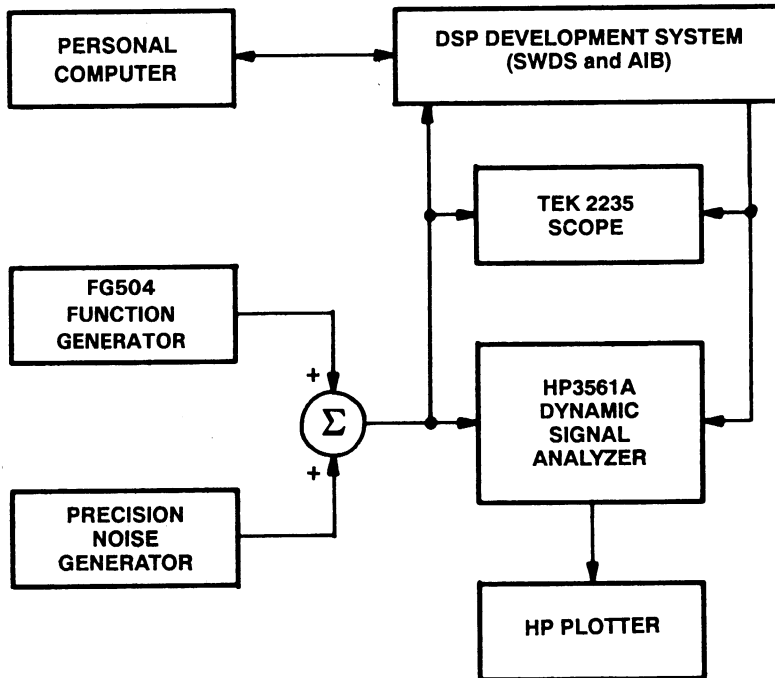


Figure 17. Real-Time Experiment Setup

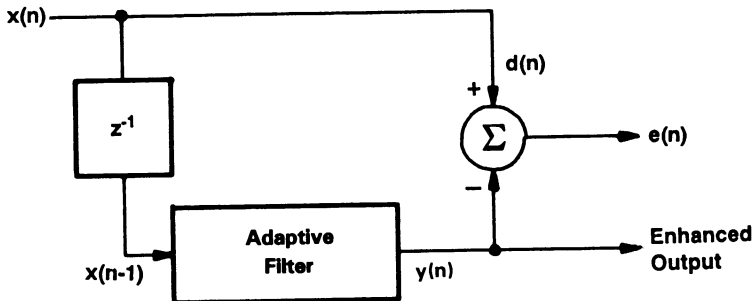


Figure 18. Block Diagram of a One-Step Adaptive Predictor

To illustrate the operation in a nonstationary environment, the adaptive predictor is implemented using a TMS320C25, and the following experiment is performed. The input signal is swept from 1287 Hz to 4025 Hz, then jumps back to 1287 Hz. The time for each sweep is one second. The input spectra at every second are shown in Figure 19a; the corresponding output spectra are shown in Figure 19b. From the observations on the

oscilloscope and signal analyzer, the significant SNR improvement, convergence speed, ability to track nonstationary signals, and long-term stability of the adaptive predictor are observed.

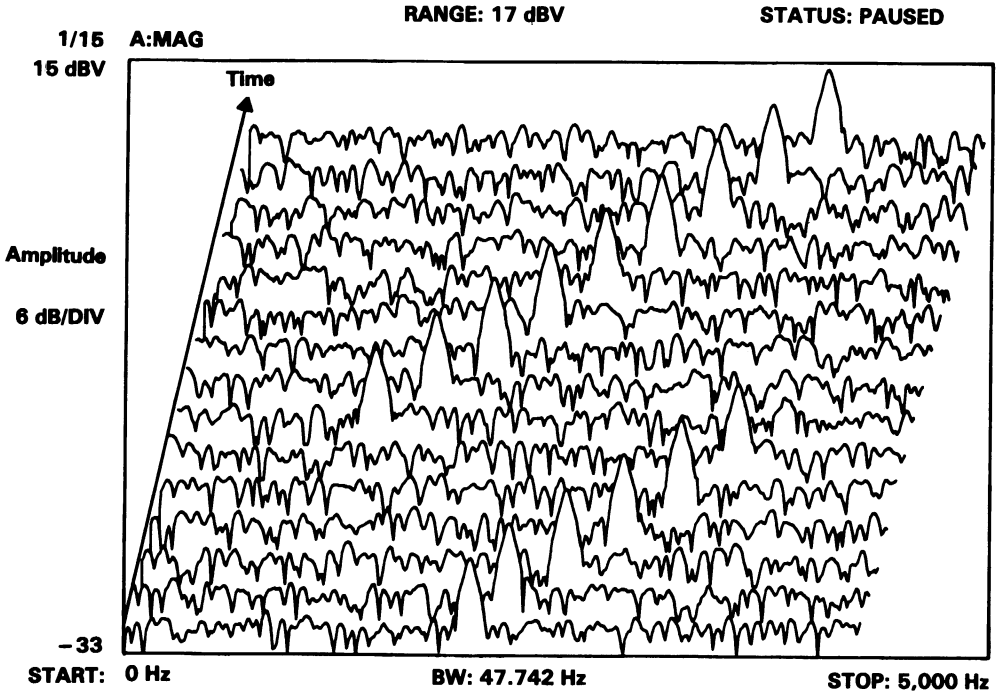
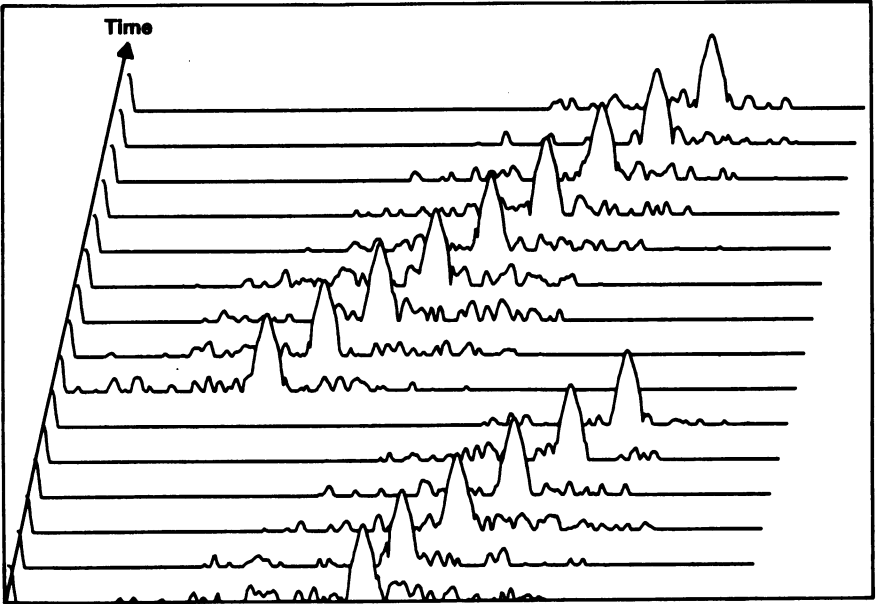


Figure 19(a). Spectrum of Input Signal

1/15 A:MAG

15 dBV

Time



START: 0 Hz

BW: 47.742 Hz

STOP: 5,000 Hz Frequency

Figure 19(b). Spectrum of Enhanced Output Signal

Summary

Three adaptive structures and six update algorithms are implemented with the TMS320C25 and TMS320C30. Applications of adaptive filters and implementation considerations have been discussed. Two subroutine libraries that support both C language and assembly language for two processors were developed. These routines can be readily incorporated into TMS320C25 or TMS320C30 users' application programs.

The advancements in the TMS320C25 and TMS320C30 devices have made the implementation of sophisticated adaptive algorithms oriented toward performing real-time processing tasks feasible. Many adaptive signal processing algorithms are readily available and capable of solving real-time problems when implemented on the DSP. These programs provide an efficient way to implement the widely used structures and algorithms on the TMS320C25 and TMS320C30, based on assembly-language programming. They are also extremely useful for choosing an algorithm for a given application. The performances of adaptive structures and algorithms that have been implemented using the TMS320C25 and TMS320C30 have been summarized in Tables 1 and 2.

Table 1. The Performance of Adaptive Structures and Algorithms of TMS320C25

TMS320C25				
Transversal Structure	LMS	Instruction Cycles	$7N + 28$	
		Program Memory (Word)	33	
	Leaky LMS	Instruction Cycles	$8N + 28$	
		Program Memory (Word)	34	
	Sign-Data LMS	Instruction Cycles	$11N + 26$	
		Program Memory (Word)	41	
	Sign-Error LMS	Instruction Cycles	$7N + 26$	
		Program Memory (Word)	30	
	Sign-Sign LMS	Instruction Cycles	$11N + 21$	
		Program Memory (Word)	30	
	Normalized LMS	Instruction Cycles	$7N + 57$	
		Program Memory (Word)	47	
	Symmetric Transversal Structure	LMS	Instruction Cycles	$7.5N + 38$
			Program Memory (Word)	50
Leaky LMS		Instruction Cycles	$8N + 38$	
		Program Memory (Word)	51	
Sign-Data LMS		Instruction Cycles	$9.5N + 36$	
		Program Memory (Word)	58	
Sign-Error LMS		Instruction Cycles	$7.5N + 36$	
		Program Memory (Word)	47	
Sign-Sign LMS		Instruction Cycles	$9.5N + 31$	
		Program Memory (Word)	47	
Normalized LMS		Instruction Cycles	$7.5N + 69$	
		Program Memory (Word)	66	
Lattice Structure		LMS	Instruction Cycles	$33N + 32$
			Program Memory (Word)	63
	Leaky LMS	Instruction Cycles	$35N + 32$	
		Program Memory (Word)	65	
	Sign-Error LMS	Instruction Cycles	$36N + 32$	
		Program Memory (Word)	65	
	Normalized LMS	Instruction Cycles	$90N + 34$	
		Program Memory (Word)	92	

Note: N represents filter order.

Table 2. The Performance of Adaptive Structures and Algorithms of TMS320C30

TMS320C30			
Transversal Structure	LMS	Instruction Cycles	$3N + 15$
		Program Memory (Word)	17
	Leaky LMS	Instruction Cycles	$3N + 15$
		Program Memory (Word)	19
	Sign-Data LMS	Instruction Cycles	$5N + 16$
		Program Memory (Word)	24
	Sign-Error LMS	Instruction Cycles	$3N + 16$
		Program Memory (Word)	18
	Sign-Sign LMS	Instruction Cycles	$5N + 16$
		Program Memory (Word)	24
Normalized LMS	Instruction Cycles	$3N + 47$	
	Program Memory (Word)	49	
Symmetric Transversal Structure	LMS	Instruction Cycles	$2.5N + 15$
		Program Memory (Word)	23
	Leaky LMS	Instruction Cycles	$2.5N + 19$
		Program Memory (Word)	26
	Sign-Data LMS	Instruction Cycles	$3.5N + 18$
		Program Memory (Word)	30
	Sign-Error LMS	Instruction Cycles	$2.5N + 18$
		Program Memory (Word)	24
	Sign-Sign LMS	Instruction Cycles	$3.5N + 17$
		Program Memory (Word)	30
Normalized LMS	Instruction Cycles	$2.5N + 50$	
	Program Memory (Word)	56	
Lattice Structure	LMS	Instruction Cycles	$14N + 9$
		Program Memory (Word)	20
	Leaky LMS	Instruction Cycles	$16N + 9$
		Program Memory (Word)	22
	Sign-Error LMS	Instruction Cycles	$16N + 9$
		Program Memory (Word)	22
	Normalized LMS	Instruction Cycles	$67N + 9$
		Program Memory (Word)	73

Note: N represents filter order.

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List of Appendices for Implementation of Adaptive Filters with the TMS320C25 and TMS320C30

Appendix	Title
A1	Transversal Structure with LMS Algorithm Using the TMS320C25
A2	Transversal Structure with LMS Algorithm Using the TMS320C30
B1	Symmetric Transversal Structure with LMS Algorithm Using the TMS320C25
B2	Symmetric Transversal Structure with LMS Algorithm Using the TMS320C30
C1	Lattice Structure with LMS Algorithm Using the TMS320C25
C2	Lattice Structure with LMS Algorithm Using the TMS320C30
D1	Transversal Structure with Normalized LMS Algorithm Using the TMS320C25
D2	Transversal Structure with Normalized LMS Algorithm Using the TMS320C30
E1	Transversal Structure with Sign-Error LMS Algorithm Using the TMS320C25
E2	Transversal Structure with Sign-Error LMS Algorithm Using the TMS320C30
F1	Transversal Structure with Sign-Sign LMS Algorithm Using the TMS320C25
F2	Transversal Structure with Sign-Sign LMS Algorithm Using the TMS320C30
G1	Transversal Structure with Leaky LMS Algorithm Using the TMS320C25
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H1	Assembly Subroutine of Transversal Structure with LMS Algorithm Using the TMS320C25
H2	Linker Command File for Assembly Main Program Calling a TMS320C25 Adaptive LMS Transversal Filter Subroutine
H3	TMS320C30 Adaptive Filter Initialization Program
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H5	Linker Command/file for Assembly Main Program Calling the TMS320C30 Adaptive LMS Transversal Filter Subroutine
I1	C Subroutine of Transversal Structure with LMS Algorithm Using the TMS320C25
I2	C Subroutine of Transversal Structure with LMS Algorithm Using the TMS320C30

Appendix A2. Transversal Structure with LMS Algorithm Using the TMS320C30

```

*****
* T30 - Adaptive transversal filter with LMS algorithm
* using the TMS320C30
*
* I/O configuration:
*
* d(n) ----->|----->|-----> e(n)
*               |----->|----->|-----> y(n)
*               |----->|----->|----->
*
* Algorithm:
*
* 63
* y(n) = SUM w(k)*x(n-k) k=0,1,2,...,63
* k=0
*
* e(n) = d(n) - y(n)
*
* w(k) = w(k) + u*e(n)*x(n-k) k=0,1,2,...,63
*
* where we use filter order = 64 and mu = 0.01.
*
* Chen, Chin-Chung March, 1989
*
*****
*.copy "adapfltr.int"
*****
* PERFORM ADAPTIVE FILTER
*****
order .set 64
mu .set 01
*****
* INITIALIZE POINTERS AND ARRAYS
*****
*.text
*.set $
LDI order,6K ; Set up circular buffer
LIP 0w_addr ; Set data page
LDI 0w_addr,AW0 ; Set pointer for x[]
LDI 0w_addr,AR1 ; Set pointer for w[]
LIP 0,0,RO ; RO = 0.0
RPTS order-1
STF RO,AW0++(1)X ; x[] = 0
:: STF RO,AW1++(1)X ; w[] = 0
LDI 0w_addr,AW6 ; Set pointer for input ports
LDI 0w_addr,AR7 ; Set pointer for output ports
*****
input:
LIP AW6,R7 ; Input d(n)
:: LIP AW6(1),R6 ; Input x(n)
STF RW,AWRO ; Insert x(n) to buffer
*
* COMPUTE FILTER OUTPUT y(n)
*
LIP 0,0,R2 ; R2 = 0.0
AW60++(1)X,AWR1++(1)X,R1
RPTS order-2
AW60++(1)X,AWR1++(1)X,R1
:: AWDF3 R1,R2,R2 ; y(n) = w[]*x[]
AWDF R1,R2 ; Include last result
*
* COMPUTE ERROR SIGNAL AND OUTPUT y(n) AND e(n) SIGNALS
*
SUBF R2,R7 ; e(n) = d(n) - y(n)
STF R2,AWR7 ; Send out y(n)
:: STF R7,AWR7(1) ; Send out e(n)
*
* UPDATE WEIGHTS w(n)
*
AWDF 0w,R7 ; R7 = e(n) * u
AWDF3 AW60++(1)X,R7,R1 ; R1 = e(n) * u * x(n)
LDI order-3,RC ; Initialize repeat counter
LMS ; Do 1 = 0, M-3
AWDF3 AW60++(1)X,R7,R1 ; R1 = e(n) * u * x(n-1)
AWDF3 AW61,R1,R2 ; R2 = w(n) + e(n) * u * x(n-1)
:: STF R2,AWR1++(1)X ; w(n+1) = w(n) + e(n) * u * x(n-1)
AWDF3 AW60,R7,R1 ; For i = N - 2
:: AWDF3 AW61,R1,R2 ; Delay branch
RD ; Delay
AWDF3 AW61,R1,R2 ; w(n+1) = w(n) + e(n) * u * x(n-1)
STF R2,AWR1++(1)X ; Update last w
*
* DEFINE CONSTANTS
*
xn .word "buffer",order
mu .usect "coeffs",order
w0 .usect "vars",1
out_addr .usect "vars",1
xn_addr .usect "vars",1
u .usect "vars",1
cinit .usect "vars",1
cinit .sect
5,ln_addr
.word 0004000h
.word 0004020h
.word xn
.word mu
.float cinit
.end

```


.end
.end
.end
.end
.end
.end
.end
.end
.end
.end

08040006
08040026

xu
an
zu
an


```

* COMPUTE THE F(I) AND B(I)
LARI      ZLAR      *ARRS
          LT      *ARR
          PPV      *ARR
          *ARR2
          SACH      *ARR2
          ZLAR      *ARR2
          PPS      *ARR2
          SACH      *ARR2

* COMPUTE DATA GAIN
          LT      U
          PPV      E
          SPN      TEMP
          LT      TEMP
          PPV      *ARR2
          *ARR2
          UVA      *ARR2
          SACH      *ARR2

NEXTI

* COMPUTE E AND UPDATE K1
          PPV      *ARR2
          *ARR2
          PPS      *ARR2
          SACH      E
          LTP      *ARR2
          PPV      *ARR2
          APAC      TEMP
          SACH      TEMP
          LTP      U
          PPV      U
          ZLAR      *ARR2
          APAC      *ARR2
          SACH      *ARR2
          BRAC      LARI,*ARR2

* COMPUTE Y
          CNP      0
          PPK      0
          ZAC      *ARR2,B1
          DLX      *ARR2
          BAC      0.000000,**
          CNP      0
          APAC      Y
          SACH      Y

*end

```

```

: ACC = F1-1
: T = k1
: P = NU * B0-1
: ACC = F1-1 + K1*B0-1, P = K1*F1-1
: Store F1
: ACC = B0-1
: ACC = B0-1 - k1 * F1-1
: Store B1

```

```

: T = NU
: P = NU * E1-1
: Store NU * E1-1
: T = NU * E1-1
: P = NU * E1-1 * B1-1
: Store E1
: ACC = G1*G1 + NU*E1-1*B1-1, T = B1
: Store G1*nt1

```

```

: P = B1 * G1
: ACC = E1-1 - B1 * G1, P = B1*F1-1
: Store E1
: T = F1, ACC = B1*F1-1
: P = F1 * B0-1
: ACC = B1*F1-1 * B0-1 * F1
: T = B1*F1-1 * B0-1 * F1
: P = NU * (F1*B0-1*F1-1*B1)
: ACC = k1*G1
: ACC = k1*G1 * NU
: Store K1*nt1

```

```

: Configure B0 as program memory
: Clear the P register
: Set the accumulator
: Set the pointer
: Configure Y (ntars)
: Configure Y
: Configure B0 as data memory
: Include last 4bits
: Store the filter output

```

FIR

*

Appendix D1. Transversal Structure with Normalized LMS Algorithm Using the TMS320C25

```

*****
.title 'TMS25'
*****
TMS25 : Adaptive Filter Using Transversal Structure
and Normalized LMS Algorithm, Leaped Code
Algorithm:
        .ds      63
        y(n) = SUM w(k)x(n-k)  k=0,1,2,...,63
        k=0
        e(n) = d(n) - y(n)
        var(k) = (1-r) * var(k-1) + r * x(n) * x(n)
        w(k) = w(k) + u*e(n)x(n-k)/var(k)  k=0,1,2,...,63
        Where we use filter order = 64 and mu = 0.01.
Notes: This source program is the generic version; I/O configuration has
not been set up. User has to modify the main routine for specific
application.
Initial conditions
1) PI status bit should be equal to 01.
2) SM status bit should be set to 1.
3) The current IP (data memory page pointer) should be page 0.
4) Data memory ONE should be 1.
5) Data memory U should be 327.
6) Data memory WR should be initialized to 07ffh.
        Chen, Chien-Chung February, 1989
*****
        .sect "parameters",1
ERR:   .sect "parameters",1
ONE:   .sect "parameters",1
U:     .sect "parameters",1
ERRF:  .sect "parameters",1
WR:    .sect "parameters",1
*****
        * PERFORM THE ADAPTIVE FILTER
        *****
        .text
        * ESTIMATE THE POWER OF SIGNAL
        LAMP   AR3
        LBLK   AR2,10
        SORR   #
        SPI    ERRF
        ZALH   VAR
        SUB    VAR,SHIFT
        AND    ERRF,SHIFT
        *
        SACK   VAR
        *
        * ESTIMATE THE SIGNAL Y
        CNFP   0
        RPKK   0
        LAC    ONE,15
        LAC    AR2,31
        RPTK   DDERP-1
        RACD   MM0/000h,-
        CNFD   APAC
        SACK   Y
        *
        * COMPUTE THE ERROR
        NEG    D
        ADDRH  D
        SACK   ERR
        *
        * UPDATE THE WEIGHTS
        LT     ERR
        "PY"   U
        PRC    ONE,15
        *
        * NORMALIZE CONVERGE FACTOR
        ARS    1A
        RPTK   VAR
        SUBC   ERRF(n); / VAR
        BIT    ERN, 0
*****

```

```

NEXT
*
BZL
MED
SACL
NEXT
ERRF
AR1_ORDER-1
LRLK
LRLK
LRLK
LT
MPY
TALR
MPVA
SACH
BANZ
*
FINISH
*
ERRF = - U * ERR(n) / VAR
; Store ERRF
; Set up counter
; Point to the coefficients
; Point to the data samples
; T register = U * ERR(n)
; P = U * ERR(n) * X(n-k)
; Load ACOE with A(k, n) & round
; M(k, n+1) = M(k, n) * P
; P = U * ERR(n) * X(n-k)
; Store M(k, n+1)
ADAPT, +=, AR2

```

Appendix D2. Transversal Structure with Normalized LMS Algorithm Using the TMS320C30

```

*****
* TMS320 - Adaptive transversal filter with Normalized LMS algorithm
* using the TMS320C30
* Algorithm:
*
*      63
*      y(n) = SUM w(i)x(n-i) i=0,1,2,...,63
*      k=0
*
*      var(n) = r*var(n-1) + (1-r)*x(n)z(n)
*
*      e(n) = d(n) - y(n)
*
*      w(k) = w(k) + u*e(n)z(n-1)/var(n) i=0,1,2,...,63
*
*      Where we use filter order = 64 and mu = 0.01.
*
*      Chen, Chin-Chang Nurch, 1989
*
*****
*.copy "adapfltr.asi"
*****
* PERFORM ADAPTIVE FILTER
*****
order      .set      64          ; Filter order
mu         .set      0.01       ; Step size
power      .set      1.0       ; Input signal power
alpha      .set      0.99%     ;
alpha      .set      0.004     ; 1.0 - alpha
*****
* INITIALIZE POINTERS AND ARRAYS
*****
.text
.set      $
LDI      order, $K
LDP      $m_addr, $
LDI      $m_addr, $M0
LDI      $m_addr, $R1
LDF      $R0, $M0
LDF      $R1, $R1
RPT      order-1
STF      $R0, $M0+($I)
:: STF      $R1, $M0+($I)
LDI      $m_addr, $M6
LDI      $m_addr, $R7
; Set pointer for input parts
; Set pointer for output parts
input:
LDF      $R6, $R7
:: LDF      $+($6($I), $R6
; $R6, $+M0

```

```

* ESTIMATE THE POWER OF THE INPUT SIGNAL
*
*      $R6, $R6
*      $R6 = $R6 * $Z
*      $R6 = (1-r) * $Z
*      $R7, $R7
*      $R7 = r * var(n-1)
*
* COMPUTE FILTER OUTPUT y(n)
*
*      LDF      $R0, $R2
*      $R2 = 0.0
*
*      $R0F3 $+M0+($I), $+R1+($I), $R1
*      :: $R0F $R6, $R7
*      RPT      $R2, $var
*      $R2 = $R2 + $var
*
*      $R0F3 $+M0+($I), $+R1+($I), $R1
*      :: $R0F3 $R1, $R2, $R2
*      $R1, $R2
*      $R1, $R2
*      ; Include last result
*
* COMPUTE ERROR SIGNAL e(n)
*
*      $R2, $R7
*      $R7 = e(n) = d(n) - y(n)
*
* OUTPUT y(n) AND e(n) SIGNALS
*
*      STF      $R2, $+R7
*      :: STF      $R7, $+R7($I)
*      ; Send out y(n)
*      ; Send out e(n)
*
* UPDATE WEIGHTS w(n)
*
*      $R5F $R3
*      $R3 = $R3
*      $R3 = $R3 - $Z
*
*      $R5F $R3
*      $R3 = $R3
*      ; Now we have 2-e-1
*
*      $R0F3 $R2, $R3, $R0
*      $R0 = $R0
*      $R0 = 2.0 - v * $X($I)
*      $R2 = $X($I) * $X($I) * (2.0 - v * $X($I))
*
*      $R0F3 $R2, $R3, $R0
*      $R0 = $R0
*      $R0 = 2.0 - v * $X($I)
*      $R2 = $X($I) * $X($I) * (2.0 - v * $X($I))
*
*      $R0F3 $R2, $R3, $R0
*      $R0 = $R0
*      $R0 = 2.0 - v * $X($I)
*      $R2 = $X($I) * $X($I) * (2.0 - v * $X($I))
*
*      $R0F3 $R2, $R3, $R0
*      $R0 = $R0
*      $R0 = 2.0 - v * $X($I)

```


Appendix E1. Transversal Structure with Sign-Error LMS Algorithm Using the TMS320C25

```

*****
.title 'TSEZ5'
*****
*
* TSEZ5 : Adaptive Filter Using Transversal Structure
* and Sign-Error LMS Algorithm ,Looped Code
*
* Algorithm
*
*      L3
*      y(n) = sum w(k)x(n-k) k=0,1,2,...,L3
*      k=0
*
*      e(n) = d(n) - Y(n)
*
*      For k = 0,1,2,...,L3
*      w(k) = w(k) + ux(n-k) if e(n) >= 0
*      w(k) = w(k) - ux(n-k) if e(n) < 0
*
*      Where we use filter order = 64 and mu = 0.01.
*
* Note: This source program is the generic version; I/O configuration has
* not been set up. User has to modify the main routine for specific
* application.
*
* Initial conditions:
* 1) PN status bit should be equal to 01.
* 2) SIM status bit should be set to 1.
* 3) The current IP (data memory page pointer) should be page 0.
* 4) Data memory ONE should be 1.
* 5) Data memory U should be 327.
* 6) Data memory NEGRO should be -327.
*
*
*      Chen, Chin-Chung February, 1989
*
*****
*
* DEFINE PARAMETERS
*
ORDER: .equ 64
PAGE0: .equ 0
*
* DEFINE ADDRESSES OF BUFFER AND COEFFICIENTS
*
Z0: .sect "buffer",ORDER-1
ZM: .sect "buffer",1
WM: .sect "coeffs",ORDER
*
* RESERVE ADDRESSES FOR PARAMETERS
*
D: .sect "parameters",1
Y: .sect "parameters",1
*****
ERR: .sect "parameters",1
ONE: .sect "parameters",1
U: .sect "parameters",1
ERR0: .sect "parameters",1
NEGRO: .sect "parameters",1
*****
* PERFORM THE ADAPTIVE FILTER
*****
.text
*
* ESTIMATE THE SIGNAL Y
*
LARP AR3
ORPK 0
LAC ONE,15
LULK AR2,1M
RPTK ORDER-1
MWD MM-OF-600M,*-
APAC
SACH Y
*
* CHECK THE SIGN OF ERROR
*
LT U
NEG D
ADDD D
BEZL NEGIT
LT NEGRO
*
* UPDATE THE WEIGHTS
*
NEXT LARK AR1,ORDER-1
LULK AR2,1M
LULK AR3,1M+1
MPY *-AR2
ZBLR *-AR3
MPYA *-,-AR2
SACH *-+0,AR1
BNWZ *-+0,AR2
*
* FINISH
*
.end
*
* Configure BO as program memory
* Clear the P register
* Using rounding
* Point to the oldest sample
* Repeat N times
* Estimate Y(n)
* Configure BO as data memory
* Store the filter output
*
* T register = U
* ACC = - Y(n)
* ACC = D(n) - Y(n)
* T register = -U
*
* Set up counter
* Point to the coefficients
* Point to the data sample
* P = U * I(n-k)
* Load ACCX with W(k,n) & round
* W(k,n*1) = W(k,n) + P
* P = U * I(n-k)
* Store W(k,n*1)

```


Appendix F1. Transversal Structure with Sign-Sign LMS Algorithm Using the TMS320C25

```

*****
.title 'TSS25'
*****
TSS : Adaptive Filter Using Transversal Structure
      and Sign-Sign LMS Algorithm ,Looped Code
Algorithms:
*****
63
y(n) = SUM w(k)x(n-k) k=0,1,2,...,63
k=0
e(n) = d(n) - y(n)
For k = 0,1,2,...,63
w(k) = w(k) + u if e(n)x(n-k) >= 0
w(k) = w(k) - u if e(n)x(n-k) < 0
where we use filter order = 64 and mu = 0.01;
Note: This source program is the generic version; I/O configuration has
not been set up. User has to modify the main routine for specific
application.
Initial condition:
1) PM status bit should be equal to 01.
2) SMR status bit should be set to 1.
3) The current DP (data memory page pointer) should be page 0.
4) Data memory ONE should be 1.
5) Data memory U should be 327.
*****
Dens, Chin-Chung February, 1989
*****
DEFINE PARAMETERS
ORDER: .equ 64
PAGE0: .equ 0
*****
DEFINE ADDRESSES OF BUFFER AND COEFFICIENTS
X0: .usect "buffer",ORDER-1
X1: .usect "buffer",1
M0: .usect "coeffs",ORDER
*****
RESERVE ADDRESSES FOR PARAMETERS
Dz: .usect "parameters",1
Yi: .usect "parameters",1
ERR: .usect "parameters",1
*****

```

```

ONE: .usect "parameters",1
U: .usect "parameters",1
ERR: .usect "parameters",1
*****
PERFORM THE ADAPTIVE FILTER
*****
.text
*****
ESTIMATE THE SIGNAL Y
LAMP AR3
OWTP
WPK 0
LAC ONE,15
L0K AR2,3M
RPK ORDER-1
R0D W0-r0d00h,s-
APIC
SACH Y
SET UP THE POINTERS
LARK AR1,ORDER-1
L0K AR2,3M
L0K AR3,3M+1
CHECK THE SIGN OF ERROR
NEG
ANDH D
SACH ERR
UPDATE THE WEIGHTS
ADAPT LAC s-0,AR2
XOR ERR
SACL ERPF
LAC ERPF
XORR RU,15
ADD s-,15
SACH SACH
BNWZ ADAPT,s-,AR3
*****
FINISH
.end
*****
Configure 80 as program memory
Clear the P register
Using rounding
Point to the oldest sample
Repeat N times
Estimate Y(n)
Configure 80 as data memory
Store the filter output
Set up counter
Point to the coefficients
Point to the data sample
ACC = D(n) - Y(n)
ACC = Y(n-k)
Get the sign of ERR(n) * Y(n-k)
Store the sign
Get the sign with its sign extension
Get the convergent factor MU or -MU
Update W(k)

```


Appendix H2. Linker Command File for Assembly Main Program Calling a TMS320C25 Adaptive LMS Transversal Filter Subroutine

```
#####  
/#####  
/ ALIAS: OBJ = COMMAND FILE FOR LINKING A TMS320C25 ASSEMBLY PROGRAM  
/#####  
/ Copyright 1988, 1989 Texas Instruments Incorporated  
/#####  
/ Usage: aspmal.obj files... -o OutFile -m CmdFile.cmd  
/#####  
/ Description: This file is a linker command file that can be used  
/ to link TMS320C25 assembly programs. Use it as  
/ a guideline. You may want to change the allocation  
/ scheme according to the size of the program and the  
/ memory configuration of your TMS320C25.  
/#####  
/ Notes:  
/ MEMORY SPECIFICATION  
/ Block B0 is configured as data memory (CODE) and  
/ RP/PC = 1 (microprocessor mode). Data memory locations  
/ 0h--50h and 80h--FFh are not configured.  
/#####  
MEMORY  
PAGE 0 : Ints : origin = 0h, length = 020h /* Program */  
PAGE 1 : Rags : origin = 0h, length = 04h /* Data */  
PAGE 2 : B0 : origin = 020h, length = 020h /* Block B0  
Int_B0M1 : origin = 0200h, length = 0100h /* B0  
Int_B0M1 : origin = 0300h, length = 0100h /* B1  
Ext_Data : origin = 0400h, length = 0FC00h  
} ;  
/#####  
/ SECTIONS ALLOCATION  
/#####  
SECTIONS  
vectors : ( ) : Ints PAGE 0 /* Interrupt vector table */  
parameters : ( ) : BlockB0 PAGE 1 /* Parameters  
coeffs : ( ) : Int_B0M1 PAGE 1 /* Block B0  
buffer : ( ) : Int_B0M1 PAGE 1 /* Block B1  
.bss : ( ) : Ext_Data PAGE 1 /* Global WMS, SIND, HELP  
} ;
```

Appendix H3. TMS320C30 Adaptive Filter Initialization Program

```

*****
width 132
*****
* This is the initial boot routine for TMS320C30 adaptive
* filter Programs.
*
* This module performs the following actions:
* 1) Allocates and initializes the system stack.
* 2) Performs auto-initialization, which copies section
*    ".const" data from ROM to DATA RAM.
* 3) Prepare to start the user's assembly program.
*
STACK_SIZE .set 40h ; Size of system stack
FP .set 003 ; Frame pointer

.section "vectors"
.word adsp_init

*
* ALLOCATE SPACE FOR THE SYSTEM STACK. INITIALIZE THE FIRST WORDS IN
* .text TO POINT TO THE STACK AND INITIALIZATION TABLES.
*
stack .usect ".stack", STACK_SIZE
.text

*
stack_addr .word stack ; Address of stack
init_addr .word cinit ; Address of init tables
*****
* ADAPTIVE FILTER INITIALIZATION ENTRY POINT FUNCTION
*****
adsp_init:
*
*
* SET UP THE INITIAL STACK POINTER
*
LUP stack_addr ; Get page of stored address
LDI EinitLaddr, #0 ; Get address of init tables
LDI SP, FP ; Load the address into SP
*****
* DO AUTOINITIALIZATION
*
LUP init_addr ; Get page of stored address
LDI EinitLaddr, #0 ; Get address of init tables
CPI -1, #0 ; If RSM mode1, skip init
BEQ done
LDI #0, #0, #0, #0 ; Get first count
BZD done ; If 0, nothing to do
LDI #0, #0, #0, #0 ; Get dest address
LDI #0, #0, #0, #0 ; Get first word
SUBI 1, #0 ; Count - 1
*****
RPTS 0 ; Block copy
de_init:
*
*
* done:
BR
*
*
* Move next count into R1
* If there is more, repeat
* Get next dest address
* Get next first word
* Count - 1
*
R0, #0, #0, #0
#R0, #0, #0, #0
R0, #0, #0, #0
de_init
#R0, #0, #0, #0
#R0, #0, #0, #0
SUBI 1, #0
begin
.end

```

Appendix H4. Assembly Subroutine of Transversal Structure with LMS Algorithm Using the TMS320C30

```

*****
* BT30 - TMS320C30 adaptive transversal filter with
* LMS algorithm assembly subroutine.
*
* Algorithm:
*
*   N-1
*   y(n) = SUM w(k)x(n-k) k=0,1,2,...,N-1
*   k=0
*
*   e(n) = d(n) - y(n)
*
*   w(k) = w(k) + u e(n)x(n-k) k=0,1,2,...,N-1
*
*   Where we use filter order = N and mu = 0.01.
*
*   Initial condition:
*
*   1) AR0 and AR1 should point to x(0) and w(0).
*   2) Data memory u should contain step size.
*   3) Data memory order should contain N-2, where N is filter order.
*   4) Data memories d, y, and e should be defined in caller routine.
*
*   Chen, Chain-Chung March, 1989
*
*****
.global LMS30,u,d,y,e,order
*
* PERFORM ADAPTIVE FILTER
*****
.text
LMS30 .set $
      PUSH R1
      PUSH R2
      PUSH R3
      PUSH R3
      PUSH R3
*
* COMPUTE FILTER OUTPUT y(n)
*
      LDF 0.0,R3 ; R3 = 0.0
*
      MPYF3 *AR0+(1)Z,AR1+(1)Z,R1
      RPTB Border
      RPTF3 *AR0+(1)Z,*AR1+(1)Z,R1
      ;; ADDF3 R1,R3,R3 ; y(n) = w(1).x(1)
*
* COMPUTE ERROR SIGNAL e(n) AND STORE y(n) AND e(n)
*
      STORE y(n)
      e(n) = d(n) - y(n)
      STORE e(n)
*
      R3 = e(n) * u
      R1 = e(n) * u * x(n)
      Initialize repeat counter
*
      Do i = 0, N-3
      R1 = e(n) * u * x(n-1-1)
      R2 = w(i) * e(n) + e(n) * u * x(n-1)
      for i = N - 2
      w(i+1) = w(i) + e(n) * u * x(n-1)
*
      R2,*AR1+(1)Z
      R1,*AR1+(1)Z
      R2,*AR1+(1)Z
      R1,*AR1+(1)Z
*
      Update last w
*
      POPF R3
      POPF R3
      POPF R2
      POPF R1
      POPF R1
*
      RETS
.end

```

Appendix H5. Linker Command/file for Assembly Main Program Calling the TMS320C30 Adaptive LMS Transversal Filter Subroutine

```

*****
/* ADMP_CMD - COMMAND FILE FOR LINKING THE320C30 ADAPTIVE FILTER */
/* PROGRAMS */
/*
/* User: tin30obj files...> cat file> > comp file> obj.cmd &
/*
/* Descriptions: This file is a sample command file that can be used
/* for linking adaptive filter assembly programs.
/* All the adaptive filter programs have to link with the
/* ADMPINIT.ASM file to do the auto-initialization.
/*
/* Notes:
/* When using the small (default) memory model, be sure
/* that the BUTRIS
/* To satisfy this, users must be smaller than 64K words and
/* must not cross any 64K boundaries.
*****
/* SPECIFY THE SYSTEM MEMORY MAP */
MEMORY
{
VECS: org = 0 len = 0x0
ROM: org = 0x0 len = 0x7FFF0
SRAM: org = 0x8000 len = 0x200 /* ROM block 0
SRAM: org = 0x8000 len = 0x200 /* System stack
RAM1: org = 0x80010 len = 0x200 /* RAM block 1
RAM2: org = 0x80040 len = 0x200 /* RAM block 2
RAM3: org = 0x80070 len = 0x200 /* RAM block 3
RAM4: org = 0x800A0 len = 0x200 /* RAM block 4
RAM5: org = 0x800D0 len = 0x200 /* RAM block 5
RAM6: org = 0x80100 len = 0x200 /* RAM block 6
RAM7: org = 0x80130 len = 0x200 /* RAM block 7
RAM8: org = 0x80160 len = 0x200 /* RAM block 8
RAM9: org = 0x80190 len = 0x200 /* RAM block 9
RAM10: org = 0x801C0 len = 0x200 /* RAM block 10
RAM11: org = 0x801F0 len = 0x200 /* RAM block 11
RAM12: org = 0x80220 len = 0x200 /* RAM block 12
RAM13: org = 0x80250 len = 0x200 /* RAM block 13
RAM14: org = 0x80280 len = 0x200 /* RAM block 14
RAM15: org = 0x802B0 len = 0x200 /* RAM block 15
RAM16: org = 0x802E0 len = 0x200 /* RAM block 16
RAM17: org = 0x80310 len = 0x200 /* RAM block 17
RAM18: org = 0x80340 len = 0x200 /* RAM block 18
RAM19: org = 0x80370 len = 0x200 /* RAM block 19
RAM20: org = 0x803A0 len = 0x200 /* RAM block 20
RAM21: org = 0x803D0 len = 0x200 /* RAM block 21
RAM22: org = 0x80400 len = 0x200 /* RAM block 22
RAM23: org = 0x80430 len = 0x200 /* RAM block 23
RAM24: org = 0x80460 len = 0x200 /* RAM block 24
RAM25: org = 0x80490 len = 0x200 /* RAM block 25
RAM26: org = 0x804C0 len = 0x200 /* RAM block 26
RAM27: org = 0x804F0 len = 0x200 /* RAM block 27
RAM28: org = 0x80520 len = 0x200 /* RAM block 28
RAM29: org = 0x80550 len = 0x200 /* RAM block 29
RAM30: org = 0x80580 len = 0x200 /* RAM block 30
RAM31: org = 0x805B0 len = 0x200 /* RAM block 31
RAM32: org = 0x805E0 len = 0x200 /* RAM block 32
RAM33: org = 0x80610 len = 0x200 /* RAM block 33
RAM34: org = 0x80640 len = 0x200 /* RAM block 34
RAM35: org = 0x80670 len = 0x200 /* RAM block 35
RAM36: org = 0x806A0 len = 0x200 /* RAM block 36
RAM37: org = 0x806D0 len = 0x200 /* RAM block 37
RAM38: org = 0x80700 len = 0x200 /* RAM block 38
RAM39: org = 0x80730 len = 0x200 /* RAM block 39
RAM40: org = 0x80760 len = 0x200 /* RAM block 40
RAM41: org = 0x80790 len = 0x200 /* RAM block 41
RAM42: org = 0x807C0 len = 0x200 /* RAM block 42
RAM43: org = 0x807F0 len = 0x200 /* RAM block 43
RAM44: org = 0x80820 len = 0x200 /* RAM block 44
RAM45: org = 0x80850 len = 0x200 /* RAM block 45
RAM46: org = 0x80880 len = 0x200 /* RAM block 46
RAM47: org = 0x808B0 len = 0x200 /* RAM block 47
RAM48: org = 0x808E0 len = 0x200 /* RAM block 48
RAM49: org = 0x80910 len = 0x200 /* RAM block 49
RAM50: org = 0x80940 len = 0x200 /* RAM block 50
RAM51: org = 0x80970 len = 0x200 /* RAM block 51
RAM52: org = 0x809A0 len = 0x200 /* RAM block 52
RAM53: org = 0x809D0 len = 0x200 /* RAM block 53
RAM54: org = 0x80A00 len = 0x200 /* RAM block 54
RAM55: org = 0x80A30 len = 0x200 /* RAM block 55
RAM56: org = 0x80A60 len = 0x200 /* RAM block 56
RAM57: org = 0x80A90 len = 0x200 /* RAM block 57
RAM58: org = 0x80AC0 len = 0x200 /* RAM block 58
RAM59: org = 0x80AF0 len = 0x200 /* RAM block 59
RAM60: org = 0x80B20 len = 0x200 /* RAM block 60
RAM61: org = 0x80B50 len = 0x200 /* RAM block 61
RAM62: org = 0x80B80 len = 0x200 /* RAM block 62
RAM63: org = 0x80BB0 len = 0x200 /* RAM block 63
RAM64: org = 0x80BE0 len = 0x200 /* RAM block 64
RAM65: org = 0x80C10 len = 0x200 /* RAM block 65
RAM66: org = 0x80C40 len = 0x200 /* RAM block 66
RAM67: org = 0x80C70 len = 0x200 /* RAM block 67
RAM68: org = 0x80CA0 len = 0x200 /* RAM block 68
RAM69: org = 0x80CD0 len = 0x200 /* RAM block 69
RAM70: org = 0x80D00 len = 0x200 /* RAM block 70
RAM71: org = 0x80D30 len = 0x200 /* RAM block 71
RAM72: org = 0x80D60 len = 0x200 /* RAM block 72
RAM73: org = 0x80D90 len = 0x200 /* RAM block 73
RAM74: org = 0x80DC0 len = 0x200 /* RAM block 74
RAM75: org = 0x80DF0 len = 0x200 /* RAM block 75
RAM76: org = 0x80E20 len = 0x200 /* RAM block 76
RAM77: org = 0x80E50 len = 0x200 /* RAM block 77
RAM78: org = 0x80E80 len = 0x200 /* RAM block 78
RAM79: org = 0x80EB0 len = 0x200 /* RAM block 79
RAM80: org = 0x80EE0 len = 0x200 /* RAM block 80
RAM81: org = 0x80F10 len = 0x200 /* RAM block 81
RAM82: org = 0x80F40 len = 0x200 /* RAM block 82
RAM83: org = 0x80F70 len = 0x200 /* RAM block 83
RAM84: org = 0x80FA0 len = 0x200 /* RAM block 84
RAM85: org = 0x80FD0 len = 0x200 /* RAM block 85
RAM86: org = 0x81000 len = 0x200 /* RAM block 86
RAM87: org = 0x81030 len = 0x200 /* RAM block 87
RAM88: org = 0x81060 len = 0x200 /* RAM block 88
RAM89: org = 0x81090 len = 0x200 /* RAM block 89
RAM90: org = 0x810C0 len = 0x200 /* RAM block 90
RAM91: org = 0x810F0 len = 0x200 /* RAM block 91
RAM92: org = 0x81120 len = 0x200 /* RAM block 92
RAM93: org = 0x81150 len = 0x200 /* RAM block 93
RAM94: org = 0x81180 len = 0x200 /* RAM block 94
RAM95: org = 0x811B0 len = 0x200 /* RAM block 95
RAM96: org = 0x811E0 len = 0x200 /* RAM block 96
RAM97: org = 0x81210 len = 0x200 /* RAM block 97
RAM98: org = 0x81240 len = 0x200 /* RAM block 98
RAM99: org = 0x81270 len = 0x200 /* RAM block 99
RAM100: org = 0x812A0 len = 0x200 /* RAM block 100
RAM101: org = 0x812D0 len = 0x200 /* RAM block 101
RAM102: org = 0x81300 len = 0x200 /* RAM block 102
RAM103: org = 0x81330 len = 0x200 /* RAM block 103
RAM104: org = 0x81360 len = 0x200 /* RAM block 104
RAM105: org = 0x81390 len = 0x200 /* RAM block 105
RAM106: org = 0x813C0 len = 0x200 /* RAM block 106
RAM107: org = 0x813F0 len = 0x200 /* RAM block 107
RAM108: org = 0x81420 len = 0x200 /* RAM block 108
RAM109: org = 0x81450 len = 0x200 /* RAM block 109
RAM110: org = 0x81480 len = 0x200 /* RAM block 110
RAM111: org = 0x814B0 len = 0x200 /* RAM block 111
RAM112: org = 0x814E0 len = 0x200 /* RAM block 112
RAM113: org = 0x81510 len = 0x200 /* RAM block 113
RAM114: org = 0x81540 len = 0x200 /* RAM block 114
RAM115: org = 0x81570 len = 0x200 /* RAM block 115
RAM116: org = 0x815A0 len = 0x200 /* RAM block 116
RAM117: org = 0x815D0 len = 0x200 /* RAM block 117
RAM118: org = 0x81600 len = 0x200 /* RAM block 118
RAM119: org = 0x81630 len = 0x200 /* RAM block 119
RAM120: org = 0x81660 len = 0x200 /* RAM block 120
RAM121: org = 0x81690 len = 0x200 /* RAM block 121
RAM122: org = 0x816C0 len = 0x200 /* RAM block 122
RAM123: org = 0x816F0 len = 0x200 /* RAM block 123
RAM124: org = 0x81720 len = 0x200 /* RAM block 124
RAM125: org = 0x81750 len = 0x200 /* RAM block 125
RAM126: org = 0x81780 len = 0x200 /* RAM block 126
RAM127: org = 0x817B0 len = 0x200 /* RAM block 127
RAM128: org = 0x817E0 len = 0x200 /* RAM block 128
RAM129: org = 0x81810 len = 0x200 /* RAM block 129
RAM130: org = 0x81840 len = 0x200 /* RAM block 130
RAM131: org = 0x81870 len = 0x200 /* RAM block 131
RAM132: org = 0x818A0 len = 0x200 /* RAM block 132
RAM133: org = 0x818D0 len = 0x200 /* RAM block 133
RAM134: org = 0x81900 len = 0x200 /* RAM block 134
RAM135: org = 0x81930 len = 0x200 /* RAM block 135
RAM136: org = 0x81960 len = 0x200 /* RAM block 136
RAM137: org = 0x81990 len = 0x200 /* RAM block 137
RAM138: org = 0x819C0 len = 0x200 /* RAM block 138
RAM139: org = 0x819F0 len = 0x200 /* RAM block 139
RAM140: org = 0x81A20 len = 0x200 /* RAM block 140
RAM141: org = 0x81A50 len = 0x200 /* RAM block 141
RAM142: org = 0x81A80 len = 0x200 /* RAM block 142
RAM143: org = 0x81AB0 len = 0x200 /* RAM block 143
RAM144: org = 0x81AE0 len = 0x200 /* RAM block 144
RAM145: org = 0x81B10 len = 0x200 /* RAM block 145
RAM146: org = 0x81B40 len = 0x200 /* RAM block 146
RAM147: org = 0x81B70 len = 0x200 /* RAM block 147
RAM148: org = 0x81BA0 len = 0x200 /* RAM block 148
RAM149: org = 0x81BD0 len = 0x200 /* RAM block 149
RAM150: org = 0x81C00 len = 0x200 /* RAM block 150
RAM151: org = 0x81C30 len = 0x200 /* RAM block 151
RAM152: org = 0x81C60 len = 0x200 /* RAM block 152
RAM153: org = 0x81C90 len = 0x200 /* RAM block 153
RAM154: org = 0x81CC0 len = 0x200 /* RAM block 154
RAM155: org = 0x81CF0 len = 0x200 /* RAM block 155
RAM156: org = 0x81D20 len = 0x200 /* RAM block 156
RAM157: org = 0x81D50 len = 0x200 /* RAM block 157
RAM158: org = 0x81D80 len = 0x200 /* RAM block 158
RAM159: org = 0x81DB0 len = 0x200 /* RAM block 159
RAM160: org = 0x81DE0 len = 0x200 /* RAM block 160
RAM161: org = 0x81E10 len = 0x200 /* RAM block 161
RAM162: org = 0x81E40 len = 0x200 /* RAM block 162
RAM163: org = 0x81E70 len = 0x200 /* RAM block 163
RAM164: org = 0x81EA0 len = 0x200 /* RAM block 164
RAM165: org = 0x81ED0 len = 0x200 /* RAM block 165
RAM166: org = 0x81F00 len = 0x200 /* RAM block 166
RAM167: org = 0x81F30 len = 0x200 /* RAM block 167
RAM168: org = 0x81F60 len = 0x200 /* RAM block 168
RAM169: org = 0x81F90 len = 0x200 /* RAM block 169
RAM170: org = 0x81FC0 len = 0x200 /* RAM block 170
RAM171: org = 0x81FF0 len = 0x200 /* RAM block 171
RAM172: org = 0x82000 len = 0x200 /* RAM block 172
RAM173: org = 0x82030 len = 0x200 /* RAM block 173
RAM174: org = 0x82060 len = 0x200 /* RAM block 174
RAM175: org = 0x82090 len = 0x200 /* RAM block 175
RAM176: org = 0x820C0 len = 0x200 /* RAM block 176
RAM177: org = 0x820F0 len = 0x200 /* RAM block 177
RAM178: org = 0x82120 len = 0x200 /* RAM block 178
RAM179: org = 0x82150 len = 0x200 /* RAM block 179
RAM180: org = 0x82180 len = 0x200 /* RAM block 180
RAM181: org = 0x821B0 len = 0x200 /* RAM block 181
RAM182: org = 0x821E0 len = 0x200 /* RAM block 182
RAM183: org = 0x82210 len = 0x200 /* RAM block 183
RAM184: org = 0x82240 len = 0x200 /* RAM block 184
RAM185: org = 0x82270 len = 0x200 /* RAM block 185
RAM186: org = 0x822A0 len = 0x200 /* RAM block 186
RAM187: org = 0x822D0 len = 0x200 /* RAM block 187
RAM188: org = 0x82300 len = 0x200 /* RAM block 188
RAM189: org = 0x82330 len = 0x200 /* RAM block 189
RAM190: org = 0x82360 len = 0x200 /* RAM block 190
RAM191: org = 0x82390 len = 0x200 /* RAM block 191
RAM192: org = 0x823C0 len = 0x200 /* RAM block 192
RAM193: org = 0x823F0 len = 0x200 /* RAM block 193
RAM194: org = 0x82420 len = 0x200 /* RAM block 194
RAM195: org = 0x82450 len = 0x200 /* RAM block 195
RAM196: org = 0x82480 len = 0x200 /* RAM block 196
RAM197: org = 0x824B0 len = 0x200 /* RAM block 197
RAM198: org = 0x824E0 len = 0x200 /* RAM block 198
RAM199: org = 0x82510 len = 0x200 /* RAM block 199
RAM200: org = 0x82540 len = 0x200 /* RAM block 200
RAM201: org = 0x82570 len = 0x200 /* RAM block 201
RAM202: org = 0x825A0 len = 0x200 /* RAM block 202
RAM203: org = 0x825D0 len = 0x200 /* RAM block 203
RAM204: org = 0x82600 len = 0x200 /* RAM block 204
RAM205: org = 0x82630 len = 0x200 /* RAM block 205
RAM206: org = 0x82660 len = 0x200 /* RAM block 206
RAM207: org = 0x82690 len = 0x200 /* RAM block 207
RAM208: org = 0x826C0 len = 0x200 /* RAM block 208
RAM209: org = 0x826F0 len = 0x200 /* RAM block 209
RAM210: org = 0x82720 len = 0x200 /* RAM block 210
RAM211: org = 0x82750 len = 0x200 /* RAM block 211
RAM212: org = 0x82780 len = 0x200 /* RAM block 212
RAM213: org = 0x827B0 len = 0x200 /* RAM block 213
RAM214: org = 0x827E0 len = 0x200 /* RAM block 214
RAM215: org = 0x82810 len = 0x200 /* RAM block 215
RAM216: org = 0x82840 len = 0x200 /* RAM block 216
RAM217: org = 0x82870 len = 0x200 /* RAM block 217
RAM218: org = 0x828A0 len = 0x200 /* RAM block 218
RAM219: org = 0x828D0 len = 0x200 /* RAM block 219
RAM220: org = 0x82900 len = 0x200 /* RAM block 220
RAM221: org = 0x82930 len = 0x200 /* RAM block 221
RAM222: org = 0x82960 len = 0x200 /* RAM block 222
RAM223: org = 0x82990 len = 0x200 /* RAM block 223
RAM224: org = 0x829C0 len = 0x200 /* RAM block 224
RAM225: org = 0x829F0 len = 0x200 /* RAM block 225
RAM226: org = 0x82A20 len = 0x200 /* RAM block 226
RAM227: org = 0x82A50 len = 0x200 /* RAM block 227
RAM228: org = 0x82A80 len = 0x200 /* RAM block 228
RAM229: org = 0x82AB0 len = 0x200 /* RAM block 229
RAM230: org = 0x82AE0 len = 0x200 /* RAM block 230
RAM231: org = 0x82B10 len = 0x200 /* RAM block 231
RAM232: org = 0x82B40 len = 0x200 /* RAM block 232
RAM233: org = 0x82B70 len = 0x200 /* RAM block 233
RAM234: org = 0x82BA0 len = 0x200 /* RAM block 234
RAM235: org = 0x82BD0 len = 0x200 /* RAM block 235
RAM236: org = 0x82C00 len = 0x200 /* RAM block 236
RAM237: org = 0x82C30 len = 0x200 /* RAM block 237
RAM238: org = 0x82C60 len = 0x200 /* RAM block 238
RAM239: org = 0x82C90 len = 0x200 /* RAM block 239
RAM240: org = 0x82CC0 len = 0x200 /* RAM block 240
RAM241: org = 0x82CF0 len = 0x200 /* RAM block 241
RAM242: org = 0x82D20 len = 0x200 /* RAM block 242
RAM243: org = 0x82D50 len = 0x200 /* RAM block 243
RAM244: org = 0x82D80 len = 0x200 /* RAM block 244
RAM245: org = 0x82DB0 len = 0x200 /* RAM block 245
RAM246: org = 0x82DE0 len = 0x200 /* RAM block 246
RAM247: org = 0x82E10 len = 0x200 /* RAM block 247
RAM248: org = 0x82E40 len = 0x200 /* RAM block 248
RAM249: org = 0x82E70 len = 0x200 /* RAM block 249
RAM250: org = 0x82EA0 len = 0x200 /* RAM block 250
RAM251: org = 0x82ED0 len = 0x200 /* RAM block 251
RAM252: org = 0x82F00 len = 0x200 /* RAM block 252
RAM253: org = 0x82F30 len = 0x200 /* RAM block 253
RAM254: org = 0x82F60 len = 0x200 /* RAM block 254
RAM255: org = 0x82F90 len = 0x200 /* RAM block 255
RAM256: org = 0x82FC0 len = 0x200 /* RAM block 256
RAM257: org = 0x82FF0 len = 0x200 /* RAM block 257
RAM258: org = 0x83000 len = 0x200 /* RAM block 258
RAM259: org = 0x83030 len = 0x200 /* RAM block 259
RAM260: org = 0x83060 len = 0x200 /* RAM block 260
RAM261: org = 0x83090 len = 0x200 /* RAM block 261
RAM262: org = 0x830C0 len = 0x200 /* RAM block 262
RAM263: org = 0x830F0 len = 0x200 /* RAM block 263
RAM264: org = 0x83120 len = 0x200 /* RAM block 264
RAM265: org = 0x83150 len = 0x200 /* RAM block 265
RAM266: org = 0x83180 len = 0x200 /* RAM block 266
RAM267: org = 0x831B0 len = 0x200 /* RAM block 267
RAM268: org = 0x831E0 len = 0x200 /* RAM block 268
RAM269: org = 0x83210 len = 0x200 /* RAM block 269
RAM270: org = 0x83240 len = 0x200 /* RAM block 270
RAM271: org = 0x83270 len = 0x200 /* RAM block 271
RAM272: org = 0x832A0 len = 0x200 /* RAM block 272
RAM273: org = 0x832D0 len = 0x200 /* RAM block 273
RAM274: org = 0x83300 len = 0x200 /* RAM block 274
RAM275: org = 0x83330 len = 0x200 /* RAM block 275
RAM276: org = 0x83360 len = 0x200 /* RAM block 276
RAM277: org = 0x83390 len = 0x200 /* RAM block 277
RAM278: org = 0x833C0 len = 0x200 /* RAM block 278
RAM279: org = 0x833F0 len = 0x200 /* RAM block 279
RAM280: org = 0x83420 len = 0x200 /* RAM block 280
RAM281: org = 0x83450 len = 0x200 /* RAM block 281
RAM282: org = 0x83480 len = 0x200 /* RAM block 282
RAM283: org = 0x834B0 len = 0x200 /* RAM block 283
RAM284: org = 0x834E0 len = 0x200 /* RAM block 284
RAM285: org = 0x83510 len = 0x200 /* RAM block 285
RAM286: org = 0x83540 len = 0x200 /* RAM block 286
RAM287: org = 0x83570 len = 0x200 /* RAM block 287
RAM288: org = 0x835A0 len = 0x200 /* RAM block 288
RAM289: org = 0x835D0 len = 0x200 /* RAM block 289
RAM290: org = 0x83600 len = 0x200 /* RAM block 290
RAM291: org = 0x83630 len = 0x200 /* RAM block 291
RAM292: org = 0x83660 len = 0x200 /* RAM block 292
RAM293: org = 0x83690 len = 0x200 /* RAM block 293
RAM294: org = 0x836C0 len = 0x200 /* RAM block 294
RAM295: org = 0x836F0 len = 0x200 /* RAM block 295
RAM296: org = 0x83720 len = 0x200 /* RAM block 296
RAM297: org = 0x83750 len = 0x200 /* RAM block 297
RAM298: org = 0x83780 len = 0x200 /* RAM block 298
RAM299: org = 0x837B0 len = 0x200 /* RAM block 299
RAM300: org = 0x837E0 len = 0x200 /* RAM block 299
}
)

/* SPECIFY THE SECTION ALLOCATION INTO MEMORY */
SECTIONS
{
vectors: 0 > VECS /* Interrupt vectors */
:reset: 0 > ROM /* Code
:const: 0 > ROM /* Initialization tables
:stack: 0 > SRAM /* System stack
:work: 0 > SRAM /* Memory for variables
:buffer: 0 > SRAM /* Memory for filter coefficients
:coeffs: 0 > RAM1 /* Memory for lattice filter gains
:parms_align(2): 0 > RAM1 /* Memory for lattice filter gains
}
)

```

Appendix II. C Subroutine of Transversal Structure with LMS Algorithm Using the TMS320C25

```

*****
.title 'LMS'
*****
CMLS : Adaptive Filter C subroutine using Transversal Structure
and LMS Algorithm, Looped Code

Algorithm:
*****
N=1
y(n) = SUM w(k)x(n-k) k=0,1,2,...,N-1
k=0
e(n) = d(n) - y(n)
w(k) = w(k) + use(n)x(n-k) k=0,1,2,...,N-1
where we use filter order = N

Usage: lms(n,mu,d,x,by,be)
n - order of filter
mu - convergence factor
d - desired signal
x - input signal
by - addr of output signal
be - addr of error signal

Note: Data memory 0200h-0300h+M-1 & 0300h-0300h+M-1 are reserved.

Chen, Chin-Chung February, 1989
*****
.def _lms
*****
RESERVE ADDRESSES FOR PARAMETERS
DBT0: .usect "parameters",1
DBT1: .usect "parameters",1
SAVE1: .usect "parameters",1
SAVE2: .usect "parameters",1
SAVE3: .usect "parameters",1
SAVE4: .usect "parameters",1
Y: .usect "parameters",1
D: .usect "parameters",1
U: .usect "parameters",1
V: .usect "parameters",1
ERR: .usect "parameters",1
ERRF: .usect "parameters",1
A0LST1: .usect "parameters",1
*****
DEFINe ADDRESSES OF BUFFER AND COEFFICIENTS
COEFFP: .equ 0f00h
COEFFD: .equ 0200h
FRSTAP: .equ 0300h
*****
PERFORM THE ADAPTIVE FILTER
*****
SAVE THE VALUES OF THE REGISTERS
*****
.text
_lms SAR AR1,SAVE1 ; Set P register shift mode
SAR SAR AR2,SAVE2 ; Set sign extension mode
SAR SAR AR3,SAVE3 ; Set overflow mode
SAR SAR AR4,SAVE4 ; Set data page = 0
SST DST0 ; Set pointer for getting parameter
SST1 DST1 ; ACC = N
*****
GET THE ADAPTIVE FILTER PARAMETERS
*****
SPW 1 ; Set P register shift mode
SSUM ; Set sign extension mode
LDPK 0 ; Set overflow mode
MRR ←← ; Set data page = 0
LAC ←← ; Set pointer for getting parameter
SUBK 1 ; ACC = N
SACL ORDER ; ORDER = N - 1
A0LX FRSTAP ; Store address of last tap
LAC A0LST ; Get and store the MU
LAC U ←← ; Get and store the D
LAC D ←← ; Get and store the D
L0LK ←←,0,AR3 ; Insert newest sample
L0LK AR3,FRSTAP
SACL ←
*****
ESTIMATE THE SIGNAL Y
*****
DNFP ; Configure B0 as program memory
MPVK 0 ; Clear the P register
L0LK 1,15 ; Using rounding
L0LK AR3,A0LST ; Point to the oldest sample
RPT ORDER ; Repeat N times
M0D COEFFP,← ; Estimate Y(n)
APAC ; Configure B0 as data memory
S0CX Y ; Store the filter output
*****
COMPUTE THE ERROR
*****
MEG D
A0Dh D
*****

```